Four Essays on German Stocks: Returns, Anomalies, and Insider Trading

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I. Motivation and Summary

Empirical research in stock markets has focused on the U.S., at least since the 1960s. This had a very positive influence on the research culture in the field of Finance and led to a number of results that were groundbreaking in the areas of asset pricing and market efficiency. However, most of these findings have been based on U.S. data, as less research is conducted with data from non-U.S. stock markets. This is unfortunate for several reasons.

As a large number of researchers use the same or very similar databases, e.g., data from the Center for Research in Security Prices (CRSP),[1] in their research on very similar topics, such as Capital-Asset-Pricing-Model (CAPM) anomalies,[2] there are concerns of data snooping and data mining (Merton (1987), Lo/MacKinlay (1990), White (2000), among others). A verification of important results, e.g., on the empirical validity of the CAPM with data from other stock markets, would increase our confidence in the reliability of the results obtained and in their 'worldwide' validity. Another potential issue is that stock markets are per se not identical, due to their cultural, institutional and regulatory differences. Some questions we might put forward could be: Why are there fewer IPOs in Germany than in the U.S. and the U.K.? Why do Germans have a preference for investing in interest-bearing assets, while U.S. citizens invest heavily in stocks? Showing and explaining such differences are important research tasks to undertake because it helps in generating appropriate laws and institutional arrangements and is needed for regulating certain industries. In addition, as research causes a stock market to become more efficient (Schwert (2003)), the U.S. market may be considered to be the most efficient. Or, put differently, because non-U.S. stock markets are less explored, their efficiency may be lower. Seeing as well-functioning stock markets are important for an economy (Levine/Zervos (1998)), research in non-U.S. stock markets is also desirable from a social perspective.

In countries like Germany or France, and particularly in smaller countries, the proportion of academics that focus their research on the U.S. stock market is probably larger than the proportion of academics that focus on their local stock market. A number of factors have contributed to this. An important one is data availability. A researcher who wants to focus on the U.S. stock market can glean a lot of interesting, high quality data from Kenneth French's website,[3] free of charge and within a short period of time. Similar websites typically either do not exist for other countries at time of writing, or, if they do exist, then the quality of the data they contain is unknown. A researcher who intends to carry out an analysis of non-U.S. markets typically has to start by spending a lot of time and resources on creating an appropriate database.

This doctoral thesis focuses on the German stock market and aims to

- contribute to a better understanding of the market in the areas of insider trading and stock market anomalies;

[1] The Center for Research in Security Prices at the University of Chicago Booth School of Business.
[2] Capital-Asset-Pricing-Model by Sharpe (1964), Lintner (1965) and Mossin (1966).
[3] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

- contribute to the availability of high quality data on the German stock market;
- point out the similarities and differences between the U.S. and German stock markets, if appropriate;
- increase interest in the German stock market;
- stimulate further research and narrow the gap between the findings known for the U.S. and Germany.

This thesis consists of four separate essays. In the remainder of this chapter, I will briefly introduce each essay, point out the main results, and describe the connections between them. The four essays are:

1) **Returns on German Stocks 1954 to 2013**, published in Credit and Capital Markets – Kredit und Kapital, 48(3), pp. 427-476, 2015 (co-authored with Richard Stehle).
2) **Non-U.S. Multi-Factor Data Sets Should be Used with Caution**, Working Paper, 2015 (co-authored with Roman Brückner, Patrick Lehmann and Richard Stehle).
3) **Trading Strategies Based on Past Returns – Evidence from Germany**, Working Paper, 2015.
4) **Do Insiders and Their Imitators Trade Profitably? Index-Specific Evidence from Germany**, Working Paper, 2015 (co-authored with Jessica King and Richard Stehle).

1) Returns on German Stocks 1954 to 2013

This paper provides a sixty-year time series of monthly returns on German stocks. The main purpose is to provide a long and accurate time series that is constructed on the basis of stable rules, is well documented, includes all return components, and is free from biases. Time series with such characteristics play an important role in several areas of Finance, but these characteristics are typically not fulfilled by existing time series on the returns of *all* German stocks.

To facilitate the quality of our time series, we compare it with other total return series and indices. As other total return series and indices cover shorter time periods and have changes in their calculation procedure, we divide the sixty years into four sub-periods and compare at least two total return series within each period. In each of the four sub-periods we study, which together cover the full sixty years, our time series is fully in line with at least one of the existing series.

Over the time period from 1954 to 2013, we estimate a geometric mean of 10.8% per year (13.8% arithmetic mean). We also look at real returns, excess returns with respect to the one-month money market interest rate, and returns for an investment horizon of twenty years. Over the full sixty years, we estimate a mean real excess return of 5.92%. In the last two non-overlapping twenty-year periods, the annual real excess returns are 5.43 and 5.34%. The historic twenty-year sub-periods have very different levels of inflation and short-term interest rates. Thus, looking at real returns or excess returns is much more appropriate than comparing nominal rates.

The second goal of the paper is to provide a detailed description of the German stock market, its peculiarities, regulation and differences as compared to the U.S. The paper provides details relating to the German stock exchanges and segments, discusses the role of preferred stocks, delistings, and penny stocks, as well as the corporate income tax credit. The third goal of the paper is to highlight the importance of the quality of the underlying data in empirical studies in general. In this context, we also give a detailed description of the stock market database by Richard Stehle. The two sections of the paper that discuss these issues (Section 2 and 3) are relevant for all four essays in this thesis and are the building blocks to which I refer many times throughout.

2) Non-U.S. Multi-Factor Data Sets Should be Used with Caution

The factors proposed by Fama/French (1993) and Carhart (1997) play an important role in the analysis of financial data. Important areas in which they are used include event studies, mutual fund performance studies, cost of equity capital estimations, and CAPM tests.

For the U.S. capital market, the calculation procedure suggested by Fama/French (1993) and the factor data supplied by Kenneth French are widely accepted and have been used in many studies. As country-specific or regional versions of a factor model seem to be more useful in explaining variations in local stock returns than they do in a world model (Griffin (2002), Fama/French (2012)), factor data have also been made available for individual non-U.S. capital markets. For some countries, only one locally created factor data set for the three- and four-factor model is freely available and, for other countries, there are several.

Exporting a specific factor model from the U.S. to other capital markets seems to be an easy and well-defined task. The construction procedures are typically well explained in the primary source and *only* need to be replicated with local data. As a consequence, alternative versions of a specific factor (model) for a specific country should be very similar and should not produce different results in applications.

In the case of Germany, to our knowledge, there are seven providers of factor sets. They all intend to fully replicate the factors proposed for the U.S. with German data. We analyze the individual factor time series of the seven providers and find that many of them are significantly different from each other. In addition, we find that the factor sets produce very different results in two standard applications. We attribute the differences among the factor data sets mainly to quality problems of the underlying databases and the fact that the factor providers typically take the specific institutional settings of the German market differently into account.

Our results show that exporting a specific factor model from the U.S. to another capital market is neither an easy nor well-defined task. Our results have implications for a range of studies that focus on international capital markets. We can well imagine that similar problems exist for other countries, especially because four of the seven providers of factors for Germany offer identically calculated factors for a large number of countries.

Based on our findings, we finally give advice to providers and users of non-U.S. factor data sets. Our recommendations should not only be relevant for researchers but also for practitioners and (commercial) data vendors.

3) Trading Strategies Based on Past Returns – Evidence from Germany

In this paper, I provide evidence on how various contrarian (De Bondt/Thaler (1985, 1987), Jegadeesh (1990), Lehmann (1990)), momentum (Jegadeesh/Titman (1993)), and seasonality strategies (Heston/Sadka (2008)) performed in the German stock market from 1965 to 2014. I contribute to the literature in two aspects. First, I carefully develop an adequate research design, which I argue is important when studying the German stock market, especially when examining the various strategies. Second, based on my methodological improvements, I obtain certain results that are different to the existing German studies as well as different to those from the U.S.

One major methodological improvement in relation to existing German studies is the use of value-weight returns. To my knowledge, all existing German studies on the returns of contrarian and momentum strategies apply equal-weighting in their portfolio formation. I find equal-weighting to be inappropriate when asking whether the strategies are accessible to investors in the context of transaction costs, liquidity, etc. Also, I find that the selection of an adequate sample of stocks, especially with respect to small stocks, is very important when analyzing the German stock market. I document that, in some time periods, more than 50% of all German stocks listed in Frankfurt[4] are smaller than €50 mio in market capitalization. Fama/French (2008) point out that such stocks can be influential particularly in equal-weight portfolios. My results document that several strategies heavily rely on small stocks, which makes these strategies difficult to implement. I also apply the standard procedure presently used in the U.S. and calculate a time series of monthly (calendar time) portfolio returns instead of buy-and-hold (abnormal) returns, more commonly applied in the older German studies, especially those that focus on long-term contrarian strategies.

Among the various strategies studied, only momentum appears to earn large and persistent non-zero returns. Over the total time period from 1965 to 2014, the classical momentum strategy based on the performance over the past two to twelve months earns a return of 1.57% per month (excluding microcap stocks and value-weight returns). In the most recent ten-year time period, it is even larger: 2.27%, which is much larger than in the U.S. However, the profitability net of transaction costs appears weak because the strategy involves trading in disproportionately small stocks with high transaction costs, especially observed for the loser portfolio. A strategy, however, that only concentrates on the winner portfolio and thus avoids the poten-

4 Stocks listed in the top and middle segment, and the former Neuer Markt.

tial problems associated with (short) selling the costly loser portfolio, appears to earn strong and persistent abnormal profits, even after transaction costs.

4) Do Insiders and Their Imitators Trade Profitably? Index-Specific Evidence from Germany

We study 11,691 publicly disclosed insider transactions by directors and officers of stock exchange-listed German companies over the time period from 2002 to 2012. The paper contributes to the literature in two aspects. First, we show that profitable insider trading is related to index membership. Second, we show how methodological variations – such as model choice, winsorizing of abnormal returns, €-volume-weighting instead of equal-weighting, and transaction costs – lead to economically and statistically different results.

In our baseline results under the standard event study methodology, we can confirm the results of former German insider trading studies: positive (negative) and statistically significant abnormal returns after purchases (sales). After taking transaction costs into account, winsorizing of abnormal returns, and under more sophisticated models, we find statistically significant abnormal returns neither for purchases nor for sales. However, after weighting the observations by their transaction volume (€-volume), for purchases we obtain a mean abnormal return of 1.65% over twenty days following the transaction day. Due to the mean delay of about only two days between the insider transaction and its publication, this and all other results typically also hold for imitators of insider transactions.

In our detailed analysis, we show that abnormal returns following insider purchases are related to index membership. Abnormal returns for purchases by insiders of stocks included in the DAX are indistinguishable from zero. For the TecDAX, on the other hand, we find that insiders and imitators earn large and statistically significant abnormal returns net of transaction costs. This result is confirmed by several robustness checks.

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II. Returns on German Stocks 1954 to 2013

Returns on German Stocks 1954 to 2013[1]

Richard Stehle[‡] and Martin H. Schmidt[‡]

Abstract

Existing time series of the returns on German stocks are either short or have weaknesses. We discuss the problems of creating such a time series and then report our monthly series based on all stocks in the top segment of the Frankfurt Stock Exchange. We compare our return series with the returns implied by major German stock market indices. In each of the four sub-periods we look at, which together cover the full 60 years, our time series is fully in line with at least one of the indices. In addition to looking at nominal rates of return we look at real returns and at excess returns with respect to the one-month money market interest rate. We show that the riskiness of a 20-year investment in German stocks, measured by the frequency of negative excess returns, has not increased but rather decreased since the middle of the 1960s.

Keywords: Germany, market portfolio, market index, long-term return, data quality, stock market peculiarities, CDAX

JEL Classification: G10

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[1] We are indebted to Anette Hartmond, Roman Brückner, Gregor Gielen, Olaf Ehrhardt, and Frank Mella for helpful discussions. Special thanks go to Frank Mella who in addition provided us with valuable historical documents. Datastream data was obtained through the RDC of CRC 649 "Economic Risk" at Humboldt University Berlin.

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III. NON-U.S. MULTI-FACTOR DATA SETS SHOULD BE USED WITH CAUTION

Non-U.S. Multi-Factor Data Sets Should be Used with Caution*‡

Roman Brückner§, Patrick Lehmann&, Martin H. Schmidt§, Richard Stehle§

Abstract

Due to the success of the Fama/French three-factor model, many factor sets for non-U.S. stock markets have been estimated and applied. Exporting a specific factor model from the U.S. to another country seems to be an easy and well-defined task. We use the example of Germany to illustrate that this is not the case. The factor sets offered by seven providers who all intend to exactly replicate the four-factor model with German data take the country-specific institutional settings into account in different ways. As a consequence of these differences and of quality problems in the underlying databases, the factor time series differ considerably and produce very different results in two standard applications. We can well imagine that similar problems exist for other countries, especially because four of the seven providers of factors for Germany offer identically calculated factors for a large number of countries. In addition to noting problems, we give advice to providers and users of non-U.S. factor sets.

Keywords: data quality, factor model, risk factors, MSCI indices, Germany

JEL Classification: G12, G15, G19

* Most factor providers have answered our questions on the details of their time series and also given us valuable comments. We are grateful for the valuable comments received from Yakov Amihud, Chris Florackis (discussant), Ioana Sima, conference participants at EFMA 2014 meeting, and seminar participants at Melbourne Business School and ESMT. Datastream and Worldscope data were obtained through the RDC of CRC 649 "Economic Risk" at Humboldt University Berlin.

‡ Earlier versions of this paper were titled "Fama/French Factors for Germany: Which Set is Best?"

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1. Introduction

The factors proposed by Fama/French (1993), SMB (small minus big stocks) and HML (high minus low book-to-market stocks) play an important role in the analysis of financial data. Together with a proxy for the market portfolio, they constitute the Fama/French three-factor model. The four-factor model additionally includes the momentum factor WML (winner minus loser stocks) proposed by Carhart (1997). Modifications and alternative factor models have been suggested in recent years and are now discussed and compared (Hou/Karolyi/Kho (2011), Cremers/Petajisto/Zitzewitz (2012), Novy-Marx (2013), among others). Recently Fama/French (2015) extended their three-factor model to a five-factor model by adding a profitability and an investment factor. It is safe to assume that factor models are here to stay, at least in the near future.

The calculation procedure suggested by Fama/French (1993) and the factor data supplied by Kenneth French[1] are widely accepted and have been used in a large number of studies focusing on the U.S. capital market. Over the years, factor data sets for the three- and four-factor model that are supposed to be exact replications have been made available for many other countries and regions as well as a worldwide unified capital market. For some countries, only one locally created factor set is available, and for other countries, there are several.[2] At least four providers offer factors for a large number of individual countries, which all may be downloaded free of charge.[3] In the case of Germany, there are seven providers of factor sets to our knowledge. Because country-specific or regional versions of a factor model seem to be more useful in explaining variations in stock returns than a world model (Griffin (2002), Fama/French (2012)), it is also safe to assume that new factors and/or factor models, which are successful in the U.S. capital market, will soon be exported to other countries.

Exporting a specific factor model from the U.S. to other capital markets appears to be an easy and well-defined task. The construction procedures are typically well explained in the primary source and *only* need to be replicated with local data. As a consequence, alternative versions of a specific factor (model) for a specific country should be very similar and should not produce different results in applications. We use the example of Germany to show that this is not the case. Exporting a specific factor model from the U.S. to another capital market is definitely not an easy or well-defined task.

We closely look at the factor data sets for the four-factor model for Germany offered by us and by other providers and also at a three-factor data set based on MSCI indices. In our comparison of the market factors, we additionally include two well-established performance indi-

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1 http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

2 E.g., Franceur (2015) provides a factor set for Canada, Ammann/Steiner (2008) for Switzerland, and Agarwalla/Jacob/Varma (2014) for India. Two locally produced factor sets exist for, e.g., the UK, one by Dimson/Nagel/Quigley (2003) and one by Gregory/Tharyan/Christidis (2013), and there are three for Germany (see Section 2.1).

3 A large number of countries are covered by the factor sets offered by Frazzini, Marmi/Poma, Lai and Schmidt/Schrimpf/von Arx/Wagner/Ziegler (2014).

ces for the German market: the CDAX, the most prominent local comprehensive performance index for Germany, and the MSCI Germany, as well as the time series for the German market available on French's website.

We find that the time series for the market portfolio and the SMB, HML and WML factors differ considerably. Even more important is that the factor sets produce very different results in two applications. In the performance analysis of 41 mutual funds that focus on German stocks, e.g., the ratio of statistically significant negative to positive fund alphas, is 8:1 according to one data set, 1:5 in another data set, and 0:0 in a third one. Additionally, the four-factor data sets typically explain mutual fund returns only marginally better than a one-factor model based on the CDAX or the MSCI Germany. In the analysis of double-sorted portfolios, all four-factor data sets do a better job than a one-factor model based on the CDAX. This illustrates that the choice between a one-factor model based on a well-established market index and a four-factor model based on a data set that has weaknesses may depend on the type of application.

Another important finding is that the factors differ much more in the earliest years we look at (1996 to 2000) than in the most recent years. This result seems to be caused mainly by the quality of the underlying data, which for most commercial databases improves over time. Most of our results seem to be caused by both the quality of the underlying data and the differences in taking country-specific institutional settings into account. The factor sets we analyze differ as a consequence of (a) the included stock exchanges, (b) the included exchange segments, (c) whether and how they deviate from the calculation procedure suggested by Fama/French due to institutional differences (e.g., the use of breakpoints), (d) their treatment of German stock market peculiarities (e.g., dual class firms and the personal tax credit for the corporate income tax), and (e) whether the proxy for the market portfolio is a publically available index or is calculated on the basis of the underlying data. The differences in taking country-specific settings into account may considerably affect the number and types of included stocks, their returns, the weights used in calculating portfolio returns, the allocation of stocks to portfolios, and as a consequence the factors. Typically, these issues are not discussed by the factor providers or others.[4]

We can well imagine that similar problems exist for other countries, especially as four of the seven providers of factors for Germany offer identically calculated factors for a large number of countries. Our analysis of the German factor data sets has many implications for providers and users of factor data sets that cover countries other than the U.S. Many of the problems we mention could be reduced or eliminated by proper precautions of users and providers. Our most important recommendations for factor users are:

[4] In the UK, some alternative ways of calculating the SMB and HML factors were proposed and compared in recent papers, especially in Michou/Mouselli/Stark (2010) and Gregory et al. (2013).

1) Compare a factor set's return on the market with a trustworthy performance index. In case of large deviations, you may replace the factor set's return on the market with a well-established performance index.
2) Check the robustness of your results by using several factor data sets (if available) and/or by using a one-factor model based on a trustworthy index.
3) Recalculate your results when updated time series become available. If the whole historic time series is not updated regularly, be especially careful when using it.

To factor providers we additionally recommend:

1) Check the quality of the underlying stock market and balance sheet databases.
2) Recalculate the whole time series whenever the underlying databases improve.
3) Perform a number of plausibility and consistency checks (check the number of included observations over time, look for outliers, etc.).
4) Pay attention to the country-specific institutional settings and provide more than one factor set if it is unclear how a specific setting should be treated.
5) Help users to identify the most important stock market indices of the covered countries and note good and easily accessible sources for these indices.
6) Possibly include a local expert in the team for each country that is covered. At least compare your procedure with the procedure used by local factor providers.

The paper proceeds as follows. The next section gives an overview of the factor data sets available for Germany. In Section 3, we discuss the differences in the factor calculation procedures and the weaknesses of the underlying stock market and balance sheet databases. Section 4 examines the different factor time series according to their characteristics and their pair-wise correlations. In Section 5, we apply the different factor sets to mutual funds that invest in German stocks and then evaluate their ability to explain the cross-sectional dispersion of average returns of 4x4 size/book-to-market and 4x4 size/momentum portfolios. The paper ends with a summary of our main results.

Because our main objective is to point out the problems providers and users of non-U.S. factor sets must face, we only put the most important and striking results in the main text. The appendices are mainly written for German providers and users. Appendix A describes the method that is used when we construct a German factor set on the basis of MSCI indices. Appendix B supplements the factor set comparisons of Section 4, and Appendix C gives advice to the users of specific factor sets for Germany.

2. Factor Data Available for Germany

2.1 Providers of Multi-Factor Data Sets

Presently, seven providers of monthly Fama/French factors exist for Germany. Some factor sets and some of the papers in which they are described have been revised at least once. We typically refer to the factor data and papers available at end of June 2013. The first three providers in the following list only offer factors for Germany, and the latter four cover several countries:[5]

(1) Artmann/Finter/Kempf/Koch/Theissen (2012), University of Cologne, University of Mannheim (this was the first freely available factor set for Germany and has been available since 2011, to our knowledge);
(2) Brückner/Lehmann/Schmidt/Stehle (2015), Humboldt University Berlin; we will refer to it as 'Our' data set.
(3) Hanauer/Kaserer/Rapp (2013), Universities of Munich and Marburg;
(4) Frazzini (2013), Stern School of Business, New York / AQR Capital Management;
(5) Lai (2013), University of Hong Kong. We do not include this data set in our analyses because it ends in 12/2010;[6]
(6) Marmi/Poma (2013), Scuola Normale Superiore di Pisa;
(7) Schmidt/Schrimpf/von Arx/Wagner/Ziegler (2014), University of Zurich, ETH Zurich, Aarhus University.

2.2 Other Possible Sources of Factor Data

Cremers et al. (2012) suggest constructing factors based on common and easily tradable size and style indices. Dyck/Lins/Pomorski (2013) use local MSCI indices to calculate local Fama/French factors in their study of the international mutual fund industry, and Cuthbertson/Nitzsche (2013) do it in their study of the German equity mutual fund industry. We also construct a factor set based on MSCI indices and check whether it can compete with factor sets based on data for individual stocks, although it is constructed differently (see Appendix A for details).

On his website, French also provides returns for three portfolios of German stocks sorted on book-to-market. The portfolios include a relatively small number of stocks before 2008. Fama/French (1998) use the portfolios as left-hand-side assets in their pricing regressions, but because the portfolios are not well diversified, they do not construct country-specific factors. We follow their lead and do not use their book-to-market portfolios to construct an HML factor for Germany. However, Bessler/Drobetz/Zimmermann (2009) and Waszczuk (2013) use the portfolios provided by French to construct an HML time series for Germany, and Wheatley/Quach (2013) do it for Australia.

Several academics have calculated and used Fama/French factors for Germany or other countries but have not made them freely available on the Internet (e.g., Ang/Hodrick/Xing/Zhang (2009), Annaert/De Ceuster/Verstegen (2013), and Busse/Goyal/Wahal (2014)). These are occasionally given to other academics on request; e.g., Dimo-

[5] We do not consider factor sets that are offered by commercial data providers or sets that are only offered on a daily basis, e.g., Eurofidai.

[6] Sandy Lai's multi-country factor data library is available at http://www.sandylai-research.com. It was used by Eun/Lai/de Roon/Zhang (2010) and Hau/Lai (2014). Lai uses the MSCI Germany as a proxy for the German market portfolio, which we think is a good idea (see Section 4.1). The other factors seem to be very similar to the factors by Schmidt et al. as her data source is also Datastream.

poulos/Wagner (2012) use the factor set of Ang et al. (2009). Some of these factor sets are calculated essentially in the same way and are based on the same stock market database as a publically available factor set.[7] Thus, our conclusions, to some extent, are also relevant for factor sets that have not been made publically available.

3. Comparison of the Factor Calculation Procedures and the Underlying Databases

The seven providers of factor data for Germany all intend to exactly replicate the four-factor model with German data. However, as we will see in the next section, the factor time series they provide differ considerably and produce very different results in two standard applications. A large part of these differences we can explain by differences in taking Germany's institutional settings into account, and by weaknesses in the underlying stock market and balance sheet databases. These aspects are summarized in Table 1 and discussed in this section.

3.1 Differences in the Factor Calculation Procedures

3.1.1 Inclusion of the Various Stock Exchanges and Exchange Segments

One hundred years ago, most industrialized countries had a number of stock exchanges. Germany had eight major stock exchanges in the 1950s, of which Düsseldorf and Frankfurt were the largest ones. The Frankfurt Stock Exchange (FSE) became more important over time and is presently by far the most important German stock exchange.[8] Four out of the six factor providers specifically state that they only include stocks traded in Frankfurt (see Panel A of Table 1). Schmidt et al. include all domestic stocks, and Frazzini does not provide details on this issue. The stocks not listed in Frankfurt typically have a low market capitalization.

All German stock exchanges maintain several segments with different listing requirements. Such segments also exist in many exchanges in other countries, e.g., NASDAQ and the London Stock Exchange. In Germany, as in most other countries, their characteristics, importance, regulation and names have been changed many times. Typically, the 100 to 150 largest stocks plus many small and very small stocks are traded in the top segment. The market capitalization of stocks traded in the middle segments and the former Neuer Markt[9] is typically lower, sometimes considerably lower. For some applications, the use of only the top segment may be preferable; for others, it may be more appropriate to use a factor set that also includes the middle segment and the former Neuer Markt. For this reason, we offer alternative factor sets: 'TOP' is based only on the stocks listed in the top segment of the FSE, 'ALL', after 1987, also includes the middle segment of the FSE and the Neuer Markt during its existence (see Panel A of Table 1). The other two local providers (Artmann et al., Hanauer et al.)

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[7] Annaert et al. (2013) note that the European data set of Schmidt et al. is very similar to theirs.

[8] See Stehle/Schmidt (2015) for a detailed description of the historical development of the German exchanges and their segments.

[9] The Neuer Markt was an exchange regulated market at the FSE from 1997 to 2003. It can be compared to the NASDAQ in New York, the AIM in London, and the Nouveau Marché in Paris (Stehle/Schmidt (2015)).

Table 1: Overview of Suppliers of Factor Data Sets for the German Stock Market

Provider/ Factor Set	Artmann/Finter/Kempf/ Koch/Theissen	Brückner/Lehmann/ Schmidt/Stehle	FrazziniA	Hanauer/Kaserer/Rapp	Marmi/Poma	Schmidt/Schrimpf/ von Arx/Wagner/Ziegler
Universities	Cologne	Humboldt	Stern School of Business, New York	Munich (TUM), Marburg	Scuola Normale Superiore, Pisa	Zurich, ETH Zürich
Online data library	http://www.cfr-cologne.de/	http://www.wiwi.hu-berlin.de/professuren/bwl/bb	http://www.econ.yale.edu/~af227/data_library.htm	http://www.fm.wi.tum.de/index.php?id=21	http://homepage.sns.it/marmi/Data_Library.html	http://www.bf.uzh.ch/cms/de/publikationen/studien/ccrs-ibf-risikofaktoren-datenbank.html
Panel A: Coverage, Data Sources						
Time period	07/1962 - 12/2012	07/1958 - 06/2014	07/1990 - 12/2014[B]	08/1996 - 01/2012[C]	07/1988 - 03/2013[D]	07/1984 - 06/2012[E]
Exchanges	Frankfurt	Frankfurt	Unknown	Frankfurt	Frankfurt	Probably all
Exchanges/ segments/ stocks	AM, NM, GM[F]	1) TOP: AM 2) ALL: AM, GM, NM, RM	Unknown	The segments included in the CDAX	Unknown	German stocks in Datastream which are “major”[G]
Data sources	KKMDB, Saling/Hoppenstedt Aktienführer[H]	Several[I]	CRSP, XpressFeed Global	Datastream, Worldscope	Factset	Datastream, Worldscope
Market Return	DAFOX until 2004, then CDAX	From the sample, value-weight	From the sample, value-weight	From the sample, value-weight	From the sample, value-weight	From the sample, value-weight
Risk free rate	One-month money market rate	One-month money market rate, EURIBOR[J]	Not available	FIBOR, EURIBOR	“Germany 3 months Treasury bill rate”	One-Month Frankfurt Banks (Middle Rate)
Panel B: Sample Selection/Breakpoints						
SMB breakpoints	Median	Median of TOP or ALL	0.8	Median	Median	0.8 and Median
HML breakpoints	0.3 / 0.7	0.3 / 0.7 of TOP or ALL	0.3 / 0.7	0.3 / 0.7	0.3 / 0.7	0.3 / 0.7
WML breakpoints, calculation	0.3 / 0.7, t-12 to t-2	0.3 / 0.7 of TOP or ALL, t-12 to t-2	0.3 / 0.7?, t-12 to t-2	0.3 / 0.7, t-12 to t-2	0.3 / 0.7, t-12 to t-2	0.3 / 0.7, t-12 to t-2
Sample selection for HML/SMB and WML	Same sample	Same sample	Unknown	Same sample	Different samples	Different samples

Provider/ Factor Set	Artmann/Finter/Kempf/ Koch/Theissen	Brückner/Lehmann/ Schmidt/Stehle	Frazzini[A]	Hanauer/Kaserer/Rapp	Marmi/Poma	Schmidt/Schrimpf/ von Arx/Wagner/Ziegler
Panel C: Included Stocks						
Dual class firms	Preferred and common stocks	Preferred and common stocks	Only common stocks	Preferred and common stocks	Only common stocks	Only common stocks
Financials	Factors: No / R_m: Yes	Factors: No / R_m: Yes	Factors: Yes / R_m: Yes	Factors: No / R_m: **No**	Factors: No / R_m: No	Factors: Yes / R_m: Yes
Tax credit	No	Yes/No	No	No	No	No
Penny stocks	Included	Delete stocks if price < 1.00 AND whose ME of firm is < 5 mln.	Unknown	Included	Stocks included if avg. traded vol. > 1,000 "on the 5 prior days"	Delete stocks with prices < 1.00 of the domestic currency
Panel D: Provided Data						
Monthly/ Daily data	Yes/No	Yes/Yes	Yes/No	Yes/No	Yes/No	Yes/No
Number of factor sets/other data	One factor set, decile and 4x4 portfolios	Six factor sets, decile, 4x4, and 2x3 portfolios, breakpoints	One factor set	One factor set	One factor set, 2x3 portfolios	Two factor sets
Multi-country factor data	No	No	Yes	No	Yes	Yes
Updates	Not updated yet	Annually, last 07/2014	Regularly	Not updated yet	Not updated yet	Times series update, last 06/2014

[A] The data provided by Frazzini is U.S. dollar returns. We use the exchange rates by the Deutsche Bundesbank (USD-DM, time series BBK01.WT5009, and from 1999 onwards USD-EUR, time series BBK01.WT5636) to calculate local returns. Note that he provides a 'market factor' (minus the one-month T-Bill). The HML time series we use in our comparison is the "standard" one as proposed by Fama/French (1992, 1993). We do not discuss the additional series "HML (devil)", Asness/Frazzini (2013).

[B] The return on the market is already available from 01/1986 and the momentum factor from 01/1987.

[C] Returns are calculated on the basis of closing prices of the first day of a month, which is unusual and may create a bias in an application as well as in our comparison with other factor providers. E.g., the row "01.01.2012" expresses the factor returns of 01 December 2011 to 01 January 2012.

[D] The momentum factor commences in 12/1988 and is surprisingly not available for a number of months in 1994, 1995 and 1996.

[E] The return on the market is already available from 12/1980, and the momentum factor is only available from 07/1987 onward.

[F] Geregelter Markt stocks (GM) only, if a stock were part of the Amtlicher Markt (AM) or Neuer Markt (NM) at a later or earlier time. (RM=Regulated Market)

[G] Domestic equity with Datastream code MAYOR="Y" and TYPE="EQ" (equity). Thus, they most likely consider stocks listed in all segments. However, this selection is based on the research lists WSCOPEBD, FGER1, FGER2, DEADBD1 and DEADBD2. With this selection, Schmidt et al. probably miss some German equities as, in addition, there are the lists FGERDOM, FGKURS and DEADBD3 to DEADBD6. Brückner (2013) discusses these selection issues in more detail.

[H] From 01/2007 onward only Datastream.

[I] Saling/Hoppenstedt Aktienführer & Kurstabellen, Börsenzeitung, HBDA, DFDB, KKMDB, Datastream, Worldscope (see Brückner et al. (2015)).

[J] The exact sources are described in Stehle/Schmidt (2015).

use a stock universe similar to our ALL. The three providers of multi-country factor data (Frazzini, Marmi/Poma, Schmidt et al.) do not specify which segments they include.

The lowest segment was traditionally the weakest in terms of regulation. It is not included in broad stock market indices and typically not included in empirical studies that focus on the German market. The three local factor providers specifically state that they do not include stocks traded in the lowest segment. The three providers of multi-country factor data do not address this question. Looking at the number of stocks included by, for example, Schmidt et al., in the year 2000 and later (see Table 2, discussed in detail in Section 3.2), we have the impression that they include the stocks listed in the lowest segments.

3.1.2 Breakpoints for Portfolio Construction

In view of the very large number of small stocks, especially on AMEX and NASDAQ, Fama/French (1993) suggest using the median of the market values of NYSE stocks to allocate the stocks from all three exchanges to the two portfolios 'small' and 'big'. As a consequence, their portfolio 'small' contains many more stocks than their portfolio 'big'[10] but still only approximately 8% of the combined market capitalization of the two size portfolios. The use of NYSE breakpoints has become a standard procedure in empirical studies focusing on the U.S. market.[11]

In the German context, breakpoints based on the top segment could be used to allocate stocks from the lower segments and the former Neuer Markt to portfolios. If information on segment membership is not available, using a size breakpoint higher than 0.5 may be an inexpensive alternative. Fama/French (2012) use the market values of world regions to allocate stocks to the 'big' and 'small' portfolios based on a breakpoint of 0.9.

A problem with the latter procedure is that the number of very small stocks that are listed in the lowest segment, expressed as a percentage of all stocks, varies strongly through time. On the FSE, it was 16% in 1998 (88/540, see Table 2) and 44% in 2012 (424/ 962). If the stocks listed in the lowest segment are included and the size breakpoint is 0.5, the SMB factor in recent years would measure mainly the difference between the lowest segment and the two higher segments and would therefore be a proxy for regulatory strength.

We believe that the choice of breakpoints is a major issue, even if stocks listed in the lowest segment are not included. We therefore offer two ALL series, one that allocates stocks according to the '50% rule' (ALL) and one with size breakpoints based on the top segment (ALL [BPs: TOP]). Schmidt et al. also discuss the breakpoint issue and provide factors using alternative size breakpoints of 0.5 and 0.8. Frazzini uses a size breakpoint of 0.8 in his inter-

[10] In 1994, e.g., the portfolio of 'small' firms of French's "U.S. Research Returns Data" (based on six portfolios formed on size and book-to-market) contains five times as many stocks.

[11] In the UK, a "natural" set of breakpoints of this type does not exist. Gregory et al. (2013, p. 177) state in this context: "Our central problem in forming the factors and portfolios is to find a UK equivalent for the NYSE break points". They further note that "the London Stock Exchange exhibits a large "tail" of small and illiquid stocks, which are almost certainly not part of the tradable universe of the major institutional investors that make up a large part of the UK market".

national factor sets. Hanauer et al. and Artmann et al. use the 50% rule (see Panel B of Table 1).

3.1.3 Data Requirements and Sample Selection

There are different data requirements for the construction of the individual factor time series. For the construction of a market time series, only a stock's market equity of the previous month and the return is required. To form momentum portfolios, in addition a return history of at least twelve month needs to be available. The size/book-to-market portfolios require the market and book equity to be available as of December of the previous year. As a consequence, the SMB, HML and WML factors may be based on a different number of stocks for specific time periods. This is the case for French's research factors for the U.S. market. Typically the number of stocks in the market time series is higher than the number of stocks in the size/momentum portfolios, which in turn is higher than the number of stocks in the size/book-to-market portfolios.

Schmidt et al. and Marmi/Poma follow French. Schmidt et al. in the early years typically use a much larger sample for the WML factor than for SMB and HML factors, probably because of missing book values. This we discuss in more detail in Section 3.2. Marmi/Poma, in many years, use a larger sample for the SMB and the HML factors, for which we do not have an explanation. Hanauer et al. use the same set of stocks for the calculation of the factor and market time series. This reduces the number of stocks in their market time series significantly compared to the other market series. The other two local providers, Artmann et al. and us, use identical samples for the SMB, HML and WML factors.

3.1.4 The Market Portfolio

All providers include a proxy for the return on the market portfolio in their factor set. All except one follow Fama/French and calculate this time series from their own sample. The exception is Artmann et al., who use the Deutscher Aktienforschungsindex (DAFOX) until 2004 and the CDAX starting in 2005. In any case, users may replace a factor set's market proxy with a proxy of their choice. The alternative market proxies for Germany are discussed by Stehle/Schmidt (2015).

3.1.5 Dual Class Firms

In the U.S., only common stocks are typically included in empirical studies and in factor calculations because U.S.-type preferred stocks are similar to bonds. German common and preferred stocks, on the other hand, are very similar and preferred stocks are very different from bonds (see Daske/Ehrhardt (2002), Stehle/Schmidt (2015)). Typically, both types of stocks are included in empirical studies on the German stock market. We argue in Section 4 that the HML factors of the different providers differ much more than the other factors because dual class firms are treated in different ways. The following approaches are feasible:

(1) Common and preferred stocks could be treated as a unit, that is, firm observations for the return and the combined market value of both enter the analysis. The return could be calculated either by one of the two types of stock prices or by both prices.
(2) Common and preferred stocks could be included as separate observations. In this case, either the book value of the equity has to be split before the book-to-market ratios are calculated or the same book-to-market is used for both.
(3) Only one stock type is included, typically the more important one. In this case, the book value of the equity has to be adjusted.

The three local factor providers all use a variant of the first approach. The three providers of multi-country factor data do not include preferred stocks. This may result in different portfolio allocations and possibly in incorrect book-to-market ratios of dual class firms.

3.1.6 Inclusion or Exclusion of Financials

Fama/French (1992) specifically exclude financials (mainly banks and insurance companies) from the portfolios that are used as test assets. In this context, they argue the following (p. 429): "We exclude financial firms because the high leverage that is normal for these firms probably does not have the same meaning as for nonfinancial firms, where high leverage more likely indicates distress." This argument refers to their inclusion of leverage variables in the set of independent variables. Because there is no leverage factor in the 1993 paper, financials are included in their factor calculation. All portfolios on French's website include financials. The British factor sets of Dimson et al. (2003) and Gregory et al. (2013) also include them.

In Germany, all local factor providers do not include financials in the factor calculation (see Panel C of Table 1). Hanauer et al. even exclude them from their market time series. Marmi/Poma also exclude them. Schmidt et al. and Frazzini include financials in all calculations.

3.1.7 The Tax Imputation System (Körperschaftsteuergutschrift)

Between 1977 and 2000, German investors received on top of their cash dividend a tax refund (corporate income tax credit), which was as valuable as the cash dividend (see Stehle/Schmidt (2015) for details). Because larger stocks and value stocks tend to pay (higher) dividends, the SMB and HML factors are affected. We provide factor sets with and without taking the corporate income tax credit into account. This allows researchers to use the proper factor set for their analyses. None of the other factor suppliers takes the corporate income tax credit into account.

3.1.8 Penny Stocks

In the U.S., penny stocks are typically delisted by the exchanges. This is not the case in Germany (Stehle/Schmidt (2015)). However, penny stocks are typically eliminated from the sample in many stock market studies. We and Schmidt et al. exclude penny stocks using slightly different procedures (see Panel C of Table 1); Artmann et al. and Hanauer et al. keep penny stocks in their sample. Frazzini and Marmi/Poma do not address this issue.

In Germany, based on our data and definition, penny stocks do not exist before 2001. Since then until recently, approximately 5% of the stocks have been penny stocks. Because of their small market value, their inclusion essentially does not affect the return on the market. However, the treatment of penny stocks affects the allocation of stocks to other portfolios and, as a consequence, the SMB and HML factor time series.

3.2 Weaknesses of the Underlying Stock Market and Balance Sheet Databases

The quality of the databases on which the U.S. factor data of French is based (CRSP and Compustat) has been discussed in a number of papers (e.g., Rosenberg/Houglet (1974), Bennin (1980), Shumway (1997)). Much less is known about the quality of the databases used in the construction of the factor data for Germany and other countries.

Schmidt et al. and Hanauer et al. use Datastream's stock market data in combination with the balance sheet data provided by Worldscope. At present, this also seems to be the most popular data source for academic studies on non-U.S. capital markets. We use it to illustrate the problems of commercial databases in our context.

The strengths and weaknesses of Datastream have been discussed in general by Ince/Porter (2006) and specifically for the German market by Brückner (2013). He "cannot recommend Datastream as the primary data source before 1990. Equity data for the time period after 1990 should be handled with care." In this section, we add to their analysis by focusing on the most crucial problem that arises in the construction of factor sets: the need to cover the chosen exchanges and segments consistently through time. If a few stocks are missing because of data limitations, this may not matter much. But an inadequate or very unstable coverage may seriously undermine the quality of a factor time series. We look at the number of stocks available on Datastream and listed on the German exchanges, at the number of stocks included in the market time series, and at the number of observations in the six size/book-to-market and six size/momentum portfolios (see Table 2).

For the end of 1987, Datastream currently only includes data on 269 of the 679 stocks that were listed on at least one German stock exchange, that is, less than 40%. Starting with 1988, the coverage increases to approximately 90%. For later years, practically all listed stocks at all exchanges and in all segments are included. The 40% at the end of 1987 is obviously not an adequate coverage of the German stock market. Brückner (2013) finds that until 1990, Datastream's coverage of large firms is considerably higher than its coverage of small firms. In addition, he reports a survivorship bias before 1990. Hence, a SMB factor based on Datastream probably changes its characteristics at this point in time.

The problem is compounded by Datastream's policy of continuously improving their data for earlier time periods. For the end of 1987, Schmidt et al. include only 209 of the 269 stocks that are currently included in Datastream. Datastream's coverage of the German market improves to 623 out of the 706 in 1988, but Schmidt et al. can extract only 406 of them for their market time series. This may be caused by extraction problems or by improvements in Data-

Table 2: Number of Listed vs. Number of Observations Included in the different Factor Sets

This table shows the total number of stocks/observations included in the market time series, size/book-to-market and size/momentum portfolios for different data suppliers as well as statistics of stock market listings in Germany (German stocks only, source: DAI Factbooks). The number of German stocks in Datastream and the CDAX are our estimates. For the number of observations included in the market time series, we do not have the data of Marmi/Poma available. The market time series of Artmann et al. is the DAFOX (until 2004, afterward CDAX), for which we only have limited data about the number of stocks included (see Göppl/Schütz (1995)). Additionally, Artmann et al. only provide 3-year intervals for their size/book-to-market and size/momentum portfolios. Frazzini does not provide a time series of the number of included observations. "na" stands for not available.

	Stock Listings								Provider/Factor Set																	
				FSE					Market Return						Size/Book-to-Market Portfolios						Size/Momentum Portfolios					
Time	Datastream	CDAX	At least one German Exchange	Top Segment	Middle Segment	Lowest Segment	Neuer Markt	Sum	Artmann et al.	French	Hanauer et al.	Our: TOP	Our: ALL	Schmidt et al.	Artmann et al.	Hanauer et al.	Marmi/Poma	Our: TOP	Our: ALL	Schmidt et al.	Artmann et al.	Hanauer et al.	Marmi/Poma	Our: TOP	Our: ALL	Schmidt et al.
1958-12	-	-	na	na	na	na	-	na	-	-	-	254	254	-	-	-	-	175	175	-	-	-	-	175	175	-
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
1987-12	269	na	679	na	na	na	-	na	263	98	-	261	282	209	*258*	-	-	175	175	116	*258*	-	-	175	175	195
1988-12	623	na	706	na	na	na	-	na	268	101	-	267	308	406	*258*	-	93	187	194	142	*258*	-	86	187	194	211
1989-12	659	na	749	na	na	na	-	na	282	113	-	280	334	481	*258*	-	130	193	220	282	*258*	-	116	193	220	468
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
1993-12	735	327	796	na	na	na	-	na	na	131	-	325	403	556	*317*	-	235	222	286	387	*317*	-	225	222	286	549
1994-12	746	334	810	na	na	na	-	na	na	131	-	334	418	563	*317*	-	120	221	286	440	*317*	-	72	221	286	550
1995-12	758	347	812	na	na	na	-	na	na	130	-	346	433	585	*317*	-	76	229	293	438	*317*	-	78	229	293	565
1996-12	758	355	802	na	na	na	-	na	na	126	203	354	434	616	*363*	203	93	225	290	444	*363*	203	91	225	290	575
1997-12	783	357	817	na	na	na	13	535?	na	127	207	356	448	636	*363*	207	99	230	293	567	*363*	207	103	230	293	612
1998-12	844	521	883	323	75	88	54	540	na	123	215	378	512	699	*363*	215	229	245	313	586	*363*	215	217	245	313	629
1999-12	1,000	671	931	359	88	93	168	708	na	115	317	409	665	908	*569*	317	236	262	351	651	*569*	317	248	262	351	709
2000-12	1,115	788	1,065	365	95	160	283	903	na	98	408	407	781	1,103	*569*	408	284	287	457	823	*569*	408	287	287	457	903
2001-12	1,117	792	1,075	359	118	163	272	912	na	109	542	398	787	1,148	*569*	542	315	290	586	978	*569*	542	346	290	586	1095
2002-12	1,054	755	1,011	333	184	152	198	867	na	104	567	369	752	1,040	*524*	567	334	277	566	870	*524*	567	292	277	566	1020
2003-12	1,012	722	976	308	376	145		829	na	119	507	342	719	981	*524*	507	266	241	506	795	*524*	507	260	241	506	975
2004-12	1,007	694	979	293	367	156	-	816	na	113	462	324	691	925	*524*	462	236	227	480	741	*524*	462	258	227	480	902
2005-12	1,021	678	976	294	354	187	-	835	na	110	441	316	673	908	*482*	441	231	215	463	715	*482*	441	262	215	463	878
2006-12	1,139	687	1,103	308	348	322	-	978	na	111	441	329	681	962	*482*	441	255	216	470	720	*482*	441	260	216	470	864
2007-12	na	685	1,171	658		387	-	1,045	na	89	437	329	684	1,013	na	437	293	224	469	779	na	437	284	224	469	937
2008-12	na	670	1,178	638	-	416	-	1,054	na	1,013	445	320	668	970	na	445	265	242	483	717	na	445	272	242	483	943
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
2013-06	na	518	na	na	-	na	-	na	-	-	-	242	516	-	-	-	-	186	389	-	-	-	-	186	389	-

stream since Schmidt et al. downloaded their data. It suggests that factor providers should update their historic time series regularly.

The problem is further compounded by the need to combine stock market and balance sheet data. We focus again on Schmidt et al. For 1987, their market time series is based on 209 stocks, their size/book-to-market portfolios are based on only 116 stocks (=55%). We believe that missing balance sheet data is the main reason for the difference. For 1988, the numbers are 406 versus 142 (=35%). It seems that the increase in the number of stock observations in Datastream is not matched by a similar increase in balance sheet data in Worldscope. By the year 2000, more than 75% of the stocks in the market time series also enter the size/book-to-market portfolios, and from then on, this percentage remains relatively stable. The changing coverage up to the year 2000 possibly leads to changes in the characteristics of the SMB and HML time series because a large number of stocks change their portfolio affiliation simply because of data availability.

Hanauer et al. only include CDAX firms in their factor calculation and start their time series in 1996. The number of stocks included in their portfolios, expressed as the number of CDAX stocks, also increases considerably over time. In 1998, only 41% (215/521) of the stocks in the CDAX are included in their portfolios, and in 2001, the figure is 68% (542/792). This we also interpret to be a consequence of the improved coverage by Worldscope. Marmi/Poma's database seems to have even larger coverage problems in its early years. In 1993, 235 stocks are included in their size/book-to-market portfolios, and two years later, there are only 76. Similar problems can be observed for their size/momentum portfolios. They include 225 observations in 1993 but only 72 in the next year. In addition, their monthly WML time series contains 16 months without a factor return (NA values) in the middle of the nineties.[12]

We and Artmann et al. use databases that were set up mainly for academic purposes. In these, the stock market data covers the chosen segments of the FSE well throughout the whole time period for which factors are provided. Additionally, both data sets appear to have stable and adequate coverage with balance sheet data.

4. Comparison of the Factor Time Series

This section compares the time series of different sets of Fama/French factors.[13] When we look at the market time series, we also include the CDAX, the MSCI Germany and French's time series for Germany. The latter two are part of multi-country data sets and therefore ideally suited for multi-country studies. We focus on the time period of 07/1996 to 12/2011, for which data for all suppliers is available. Table 3 shows descriptive statistics of the different

[12] Unfortunately, we cannot report numbers for Frazzini because we only know the mean number of stocks included in the factor set: 662 stocks for the time period of 1989 to 2011 (Asness/Frazzini (2013)). Also, for Marmi/Poma, we do not have access to the number of stocks included in the calculation of their market time series.

[13] We do not include a comparison of the risk-free rates provided by the suppliers, as they are essentially identical. However, we always use our estimates of the risk free rate to calculate market excess returns (R_m - R_f).

Table 3: Descriptive Statistics of Factor Time Series

The descriptive statistics are all based on the time period of 1996/07 to 12/2011 (186 month) for which the data of all suppliers are available. The construction of factors based on MSCI indices is described in Appendix A. Our TOP includes only the top segment, ALL also includes the middle segment and the former Neuer Markt, both without the tax credit. BP stands for breakpoint. Asterisks ***/**/* show significance at the 1/5/10% level. The largest and smallest values within each panel and column are colored grey.

Provider/Factor Set	Min	0.25	Median	0.75	Max	Mean	Sd	Kurt	Skew
				Panel A: R_m-R_f					
Artmann et al.	-20.98	-2.92	1.31	4.35	17.37	0.53	5.99	4.44	-0.53
CDAX	-24.12	-3.24	1.11	4.38	19.80	0.40	6.42	4.53	-0.56
Frazzini	-17.06	-2.65	0.71	3.65	15.97	0.28	5.67	3.73	-0.39
French	-24.17	-2.94	0.75	4.54	19.12	0.44	6.23	4.49	-0.53
Hanauer et al.	-15.49	-2.61	1.25	4.60	13.83	0.56	5.92	3.17	-0.53
Marmi/Poma	-11.45	-1.72	0.63	2.55	22.02	0.31	4.11	7.31	0.54
MSCI	-25.20	-3.17	1.05	4.93	20.73	0.45	6.74	4.47	-0.51
Our: TOP	-21.60	-2.87	1.15	4.17	17.44	0.46	5.85	4.35	-0.52
Our: ALL	-21.59	-2.99	1.35	4.10	17.32	0.42	5.91	4.21	-0.49
Schmidt et al.	-16.46	-2.75	0.53	4.08	14.70	0.39	5.61	3.51	-0.56
				Panel B: SMB					
Artmann et al.	-12.96	-3.05	-0.46	2.25	10.61	-0.55*	4.00	3.36	-0.21
Frazzini	-13.66	-2.50	-0.4	2.78	12.30	-0.03	4.05	3.40	0.06
Hanauer et al.	-14.30	-3.36	-0.65	2.41	10.36	-0.71**	4.14	3.03	-0.23
Marmi/Poma	-11.74	-2.76	-0.62	1.36	24.91	-0.56*	3.99	11.49	1.43
MSCI	-14.33	-2.01	-0.06	2.22	7.43	-0.09	3.57	4.77	-0.71
Our: TOP	-14.02	-3.19	-0.48	2.67	9.61	-0.32	4.06	3.06	-0.18
Our: ALL [BPs: TOP]	-14.55	-3.39	-0.48	2.31	8.58	-0.48*	3.84	3.10	-0.21
Our: ALL	-15.03	-3.45	-1.31	1.84	11.33	-0.80***	4.08	3.38	0.02
Schmidt et al. [size-BP: 0.5]	-10.50	-3.02	-0.26	1.98	12.98	-0.28	3.90	3.41	0.23
Schmidt et al. [size-BP: 0.8]	-10.26	-2.43	-0.3	1.76	9.79	-0.27	3.39	3.29	0.06
				Panel C: HML					
Artmann et al.	-12.24	-1.21	0.75	2.77	19.23	0.85***	3.93	6.67	0.43
Frazzini	-12.38	-2.61	0.19	3.74	15.59	0.67*	4.65	3.61	0.40
Hanauer et al.	-10.36	-1.48	0.37	2.89	11.91	0.74***	3.49	3.79	0.32
Marmi/Poma	-15.15	-1.20	1.10	2.64	19.00	1.13***	4.06	6.89	0.61
MSCI	-20.75	-1.80	0.42	2.16	12.98	0.24	4.50	6.52	-0.62
Our: TOP	-13.16	-1.03	0.47	2.71	15.62	0.42*	3.46	6.05	-0.05
Our: ALL [BPs: TOP]	-15.95	-1.07	0.55	2.57	16.14	0.64**	3.70	7.37	0.07
Our: ALL	-12.85	-1.00	0.62	2.40	14.34	0.76***	3.51	6.02	0.34
Schmidt et al. [size-BP: 0.5]	-8.76	-1.48	0.57	2.65	11.03	0.55**	3.68	3.56	0.31
Schmidt et al. [size-BP: 0.8]	-14.74	-1.05	0.81	2.59	13.47	0.77***	3.86	5.57	-0.08
				Panel D: WML					
Artmann et al.	-21.51	-0.1	1.52	3.30	17.55	1.44***	5.21	7.32	-0.68
Frazzini	-23.71	-2.05	1.52	4.34	30.62	1.24**	7.25	5.95	-0.12
Hanauer et al.	-40.71	-1.64	1.53	3.86	19.99	1.19**	7.02	11.09	-1.48
Marmi/Poma	-23.19	-1.01	1.28	4.23	20.68	1.60***	6.12	5.61	-0.10
Our: TOP	-20.40	-1.29	1.04	3.54	21.81	1.32***	5.26	6.94	-0.21
Our: ALL [BPs: TOP]	-21.29	-0.80	1.25	3.61	20.30	1.34***	5.66	6.22	-0.30
Our: ALL	-32.93	-1.32	1.34	3.73	22.43	1.05**	6.63	8.74	-1.11
Schmidt et al. [size-BP: 0.5]	-32.91	-0.80	1.68	3.63	18.97	1.31***	6.63	9.24	-1.31
Schmidt et al. [size-BP: 0.8]	-37.54	-1.18	1.39	4.33	21.95	1.27**	7.23	8.99	-1.14

Table 4: Factor Time Series Analyses and Tests of Equality of Means

This table shows R^2s and test statistics (p-values) for pair-wise mean (t-test) and mean rank (Wilcoxon-test) tests between factor time series of different providers. We use the factor set by Schmidt et al. with size breakpoint 0.8 and our factor set 'ALL' with breakpoints from the top segment without the tax credit. The construction of factors based on MSCI indices is described in Appendix A. The R^2's are from simple OLS regressions where the left hand variable is a factor time series of column one regressed on a time series of another supplier. The analysis is based on the time period of 07/1996 to 12/2011 (186 month). Values below 0.5 (0.3) for the R^2s and values below 0.1 (0.05) for the p-values of test statistics are colored (dark) grey.

Provider/ Factor Set	R^2									T-test (p-values)									Wilcoxon-test (p-values)								
	Artmann et al.	CDAX	Frazzini	French	Hanauer et al.	Marmi/ Poma	MSCI	Our: ALL	Schmidt et al.	Artmann et al.	CDAX	Frazzini	French	Hanauer et al.	Marmi/ Poma	MSCI	Our: ALL	Schmidt et al.	Artmann et al.	CDAX	Frazzini	French	Hanauer et al.	Marmi/ Poma	MSCI	Our: ALL	Schmidt et al.
Panel A: R_m-R_f																											
Artmann et al.	1.00	0.97	0.88	0.94	0.82	0.49	0.96	0.97	0.86		0.13	0.11	0.42	0.87	0.49	0.49	0.17	0.43		0.61	0.09	0.44	0.75	0.44	0.51	0.15	0.34
CDAX		1.00	0.91	0.98	0.85	0.49	0.99	0.98	0.89			0.43	0.54	0.38	0.80	0.32	0.74	1.00			0.29	0.78	0.24	0.80	0.52	0.97	0.93
Frazzini			1.00	0.90	0.80	0.45	0.90	0.91	0.82				0.28	0.16	0.93	0.31	0.28	0.52				0.20	0.07	0.83	0.17	0.24	0.32
French				1.00	0.85	0.47	0.99	0.97	0.88					0.51	0.70	0.84	0.83	0.79					0.33	0.78	0.54	0.90	0.96
Hanauer et al.					1.00	0.42	0.84	0.85	0.96						0.45	0.60	0.43	0.08						0.51	0.34	0.43	0.06
Marmi/Poma						1.00	0.46	0.50	0.48							0.70	0.71	0.77							0.68	0.70	0.84
MSCI							1.00	0.97	0.88								0.77	0.76								0.94	0.97
Our: ALL								1.00	0.89									0.86									0.76
Schmidt et al.									1.00																		
Panel B: SMB																											
Artmann et al.	1.00		0.33		0.77	0.07	0.33	0.74	0.51			0.06		0.30	0.99	0.07	0.62	0.17			0.02		0.47	0.64	0.05	0.82	0.36
Frazzini			1.00		0.26	0.01	0.16	0.33	0.30					0.02	0.19	0.86	0.10	0.38					0.03	0.08	0.81	0.07	0.53
Hanauer et al.					1.00	0.07	0.24	0.65	0.56						0.68	0.03	0.21	0.03						0.88	0.03	0.17	0.06
Marmi/Poma						1.00	0.02	0.04	0.04							0.19	0.82	0.40							0.11	0.68	0.31
MSCI							1.00	0.41	0.33								0.09	0.44								0.07	0.18
Our: ALL								1.00	0.56									0.28									0.41
Schmidt et al.									1.00																		
Panel C: HML																											
Artmann et al.	1.00		0.22		0.49	0.18	0.16	0.47	0.42			0.58		0.60	0.37	0.08	0.35	0.76			0.29		0.53	0.75	0.20	0.41	0.78
Frazzini			1.00		0.21	0.04	0.10	0.29	0.20					0.83	0.25	0.28	0.93	0.75					0.50	0.19	0.75	0.66	0.31
Hanauer et al.					1.00	0.06	0.12	0.44	0.37						0.25	0.15	0.66	0.87						0.40	0.18	0.91	0.69
Marmi/Poma						1.00	0.04	0.15	0.07							0.03	0.12	0.32							0.04	0.42	0.49
MSCI							1.00	0.20	0.16								0.21	0.12								0.09	0.01
Our: ALL								1.00	0.44									0.56									0.64
Schmidt et al.									1.00																		
Panel D: WML																											
Artmann et al.	1.00		0.60		0.69	0.55		0.63	0.66			0.55		0.37	0.62		0.68	0.57			0.22		0.73	0.87		0.66	0.87
Frazzini			1.00		0.57	0.32		0.67	0.61					0.88	0.44		0.75	0.94					0.51	0.34		0.58	0.54
Hanauer et al.					1.00	0.37		0.74	0.83						0.34		0.56	0.71						0.48		0.95	0.74
Marmi/Poma						1.00		0.33	0.34								0.52	0.47								0.40	0.80
Our: ALL								1.00	0.71									0.80									0.58
Schmidt et al.									1.00																		

time series, and Table 4 shows R^2s from simple OLS regressions where the left hand variable is a factor time series regressed on a time series of another supplier. Table 4 also contains *p*-values obtained from pair-wise t-tests and Wilcoxon tests to determine if the means or mean ranks of two time series differ significantly from each other. Figures 1 to 4 show rolling means of factor time series, where each observation is based on the prior 60 months. Appendix B in addition contains a detailed analysis of significant differences among the factor time series and a list of the largest monthly differences.

4.1 The Return on the Market

At first glance, the average monthly excess returns on the market differ considerably. They vary between 0.28% (Frazzini) and 0.56% (Hanauer et al.; see Panel A of Table 3). The Wilcoxon test rejects the null hypothesis that these two time series have equal means on a 10% level, and the standard t-test is close to a rejection (see Panel A of Table 4). Both tests also reject the null that the time series of Schmidt et al. and Hanauer et al. have equal means.

However, six of the ten time series have relatively similar means: CDAX, MSCI, French, Schmidt et al., our TOP and our ALL. They are all between 0.39% and 0.46% for the time period 07/1996 to 12/2011. This implies a market risk premium of 5% to 6% per year. The CDAX, Schmidt et al. and our ALL estimate are at the lower end, 0.39% to 0.42%, probably because more small stocks and especially the stocks listed in the former Neuer Markt are included. The MSCI, French's time series[14] and our TOP concentrate on larger stocks. They have higher mean returns (0.44% to 0.46%), which reflects the reverse size effect prevalent in Germany (Stehle (1997), Amel-Zadeh (2011)).

The low mean returns on the market time series of Frazzini (0.28%) and Marmi/Poma (0.31%) are possibly because the underlying databases do not include <u>all</u> cash and stock dividends, stock splits, rights issues, etc. All of these contribute significantly to the return on German stocks. In the case of Frazzini, this view is supported by a significant change in the factor time series after a recent update. The numbers we mainly report were taken from his website in June 2013. As a result of subsequent changes in the factor time series, the mean excess return on the market increases from 0.28% to 0.37%, which is much more in line with the other means. For the other factor time series calculated by Frazzini, the change is even more dramatic (see below).

The estimates for Hanauer et al. and Artmann et al. are considerably higher than the other means. Hanauer et al.'s high mean is probably caused by the exclusion of financials that did not perform well in the time period we consider. Artmann et al. use the DAFOX as their market proxy until 2004; its high mean we attribute to the DAFOX error in 1998 (Stehle/Schmidt

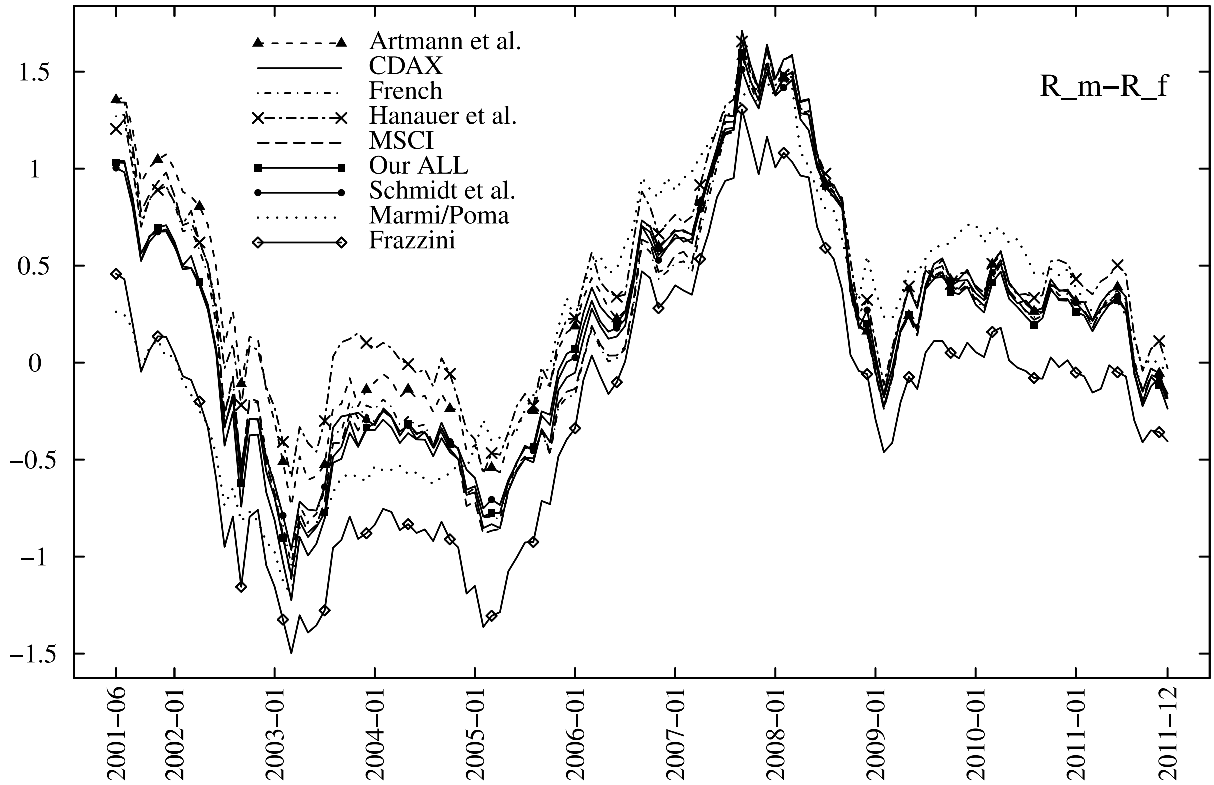
[14] The market proxy provided by French contains a very large increase in the number of included stocks in 2008. In 2007, the market time series is based on 89 stocks; in the following year, on 1,013; see Table 2.

(2015)) and the non-inclusion of the former Neuer Markt stocks, which did not do well either.[15]

The weaknesses of the market proxies of Frazzini and Marmi/Poma, the "1998-problem" of the Artmann et al. proxy, and the special character of the Hanauer et al. proxy (no financials) are confirmed by the rolling factor means shown in Figure 1. In the first 5-year period, which ends in 06/2001, the means of the time series provided by Marmi/Poma and by Frazzini are considerably lower than all others. Artmann et al.'s series has the highest mean. The rolling mean of Frazzini remains considerably lower than the others until the end of our observation period. The rolling 5-year means of the other time series differ from each other by less than 0.3%-points in the first 5-year period. In the years ending after 01/2008, all rolling means except Marmi/Poma, Frazzini and Hanauer et al. are nearly identical.

Figure 1: Rolling Means of Nine Market Excess Return Time Series

Each point in this graph is based on the prior 60 months, starting in 06/2001 (including the time period of 07/1996 to 06/2001).



Our results are confirmed by an analysis of the pairwise correlation coefficients (see Panel A of Table 4). To conserve space, we only include our factor set ALL with breakpoints from the top segment and the Schmidt et al. set with a size-breakpoint of 0.8 in this analysis. The time series that have the most similar means and rolling means (CDAX, MSCI, French, our ALL) also have the highest pairwise correlation coefficients (R^2 = 0.97 and higher). The cor-

[15] In their empirical test of the CAPM, Artmann et al. include Neuer Markt stocks in their left-hand side portfolios. This and the use of the DAFOX on the right-hand side may have caused their conclusion that "none of the models [CAPM, three-factor, four-factor] can consistently explain the cross-section of [German] returns."

relation coefficients of the series offered by Artmann et al., Hanauer et al., Schmidt et al. and Frazzini are a bit lower. The latter one performs well here because its rolling mean is consistently below the others. Marmi/Poma's pairwise R^2s are all below 0.5.

4.2 The SMB Time Series

The differences between the means of the SMB time series are even larger than the differences between the means of the market excess returns. Our ALL series with breakpoints 0.5, the series of Hanauer et al. and of Artmann et al. have the lowest means (-0.80%, -0.71% and -0.55%; see Panel B of Table 3). These three time series are constructed in similar ways.

On the other hand, the SMB time series of Frazzini and the series based on MSCI indices have means very close to zero (-0.03%, -0.09%). Based on the new data on Frazzini's website, the mean is 0.60%. After this twenty-fold increase, his mean is much more in line with the other means. However, the null hypothesis that the two groups of time series (ALL, Artmann et al., Hanauer et al. versus Marmi/Poma and MSCI) have equal means is rejected in six pair-wise tests by both the standard t-test and the Wilcoxon test (see Panel B of Table 4).

Also rejected is the null hypothesis that the SMB time series of Schmidt et al. and Hanauer et al. have equal means. This should be related to the fact that their underlying samples differ in many aspects,[16] although both use Datastream and Worldscope as their data source. Judged by its mean, the SMB time series of Marmi/Poma seems to be reasonably good (-0.56%), but its skewness and kurtosis, which are considerably higher than the other estimates, point to problems in this time series (see Panel B of Table 3).

In the SMB figure (Figure 2), the rolling means differ more in 06/2001 than in 12/2011 (1.0 vs. 0.5%-points). Hence, the nine series included in the graph become more similar over time. The rolling mean of Frazzini is at the top at the beginning and at the end. Our ALL series is at the bottom at the beginning and at the end and is closely accompanied by the series of Hanauer et al. and Artmann et al. Note that all SMB time series agree that a reverse size effect exists and is most pronounced from 1996 to 2001. It disappeared after 2001.

The correlation between the SMB time series is much lower than the correlation between the market time series. The lowest R^2 between any pair of time series is 0.01 (Frazzini and Marmi/Poma), and the highest is 0.77 (Artmann et al. and Hanauer et al., see Panel B of Table 4). (In this part of the table, R^2s below 0.5 are colored grey, and R^2s below 0.3 are colored dark grey.) The SMB time series of Marmi/Poma is practically uncorrelated with all other SMB time series.

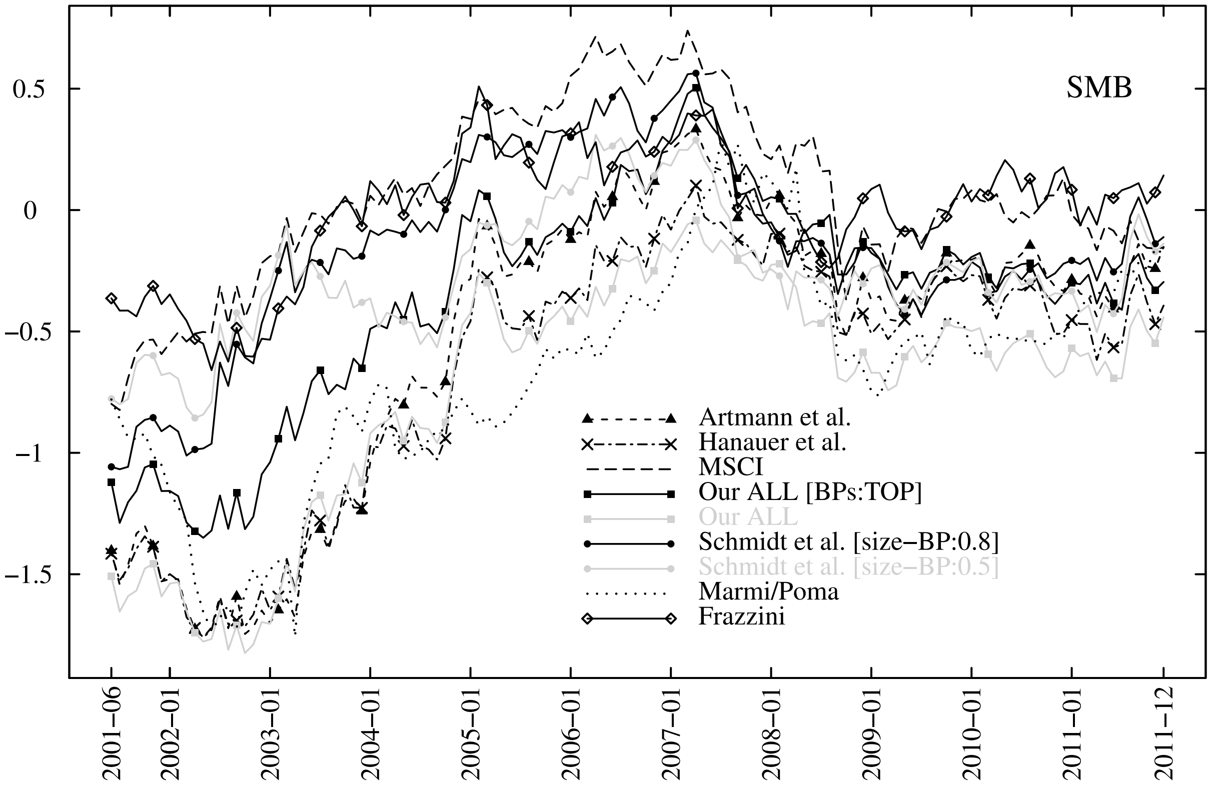
Our two time series for the SMB factor, which include all segments but differ with respect to the breakpoints used – that is, our factor sets ALL and ALL [BP: TOP] – differ considerably from each other: The means are -0.48% versus -0.80%. This shows that the choice of breakpoints is an important issue (see Section 3.1.2 for a discussion). Schmidt et al.'s two

[16] For example, Schmidt et al. has a much larger sample and include financials, while Hanauer et al. do not include financials in the market time series and the factors.

SMB time series, which are identical in every respect except the size-breakpoint (0.5 and 0.8), have nearly identical means, however.

Figure 2: Rolling Means of Nine SMB Time Series

Each point in this graph is based on the prior 60 months, starting in 06/2001 (including the time period of 07/1996 to 06/2001).



4.3 The HML Time Series

The HML time series of Marmi/Poma has the highest mean (1.13%), the time series based on MSCI indices has the lowest (0.24%; see Panel C of Table 3). Both the standard t-test and the Wilcoxon test reject the null hypothesis of equal means at the 5% level (see Panel C of Table 4). The other means vary between 0.42% (our TOP) and 0.85% (Artmann et al.). Frazzini's updated time series is considerably different from the initial one (0.67% vs. 0.94%); this time it moves away from the other series, however.

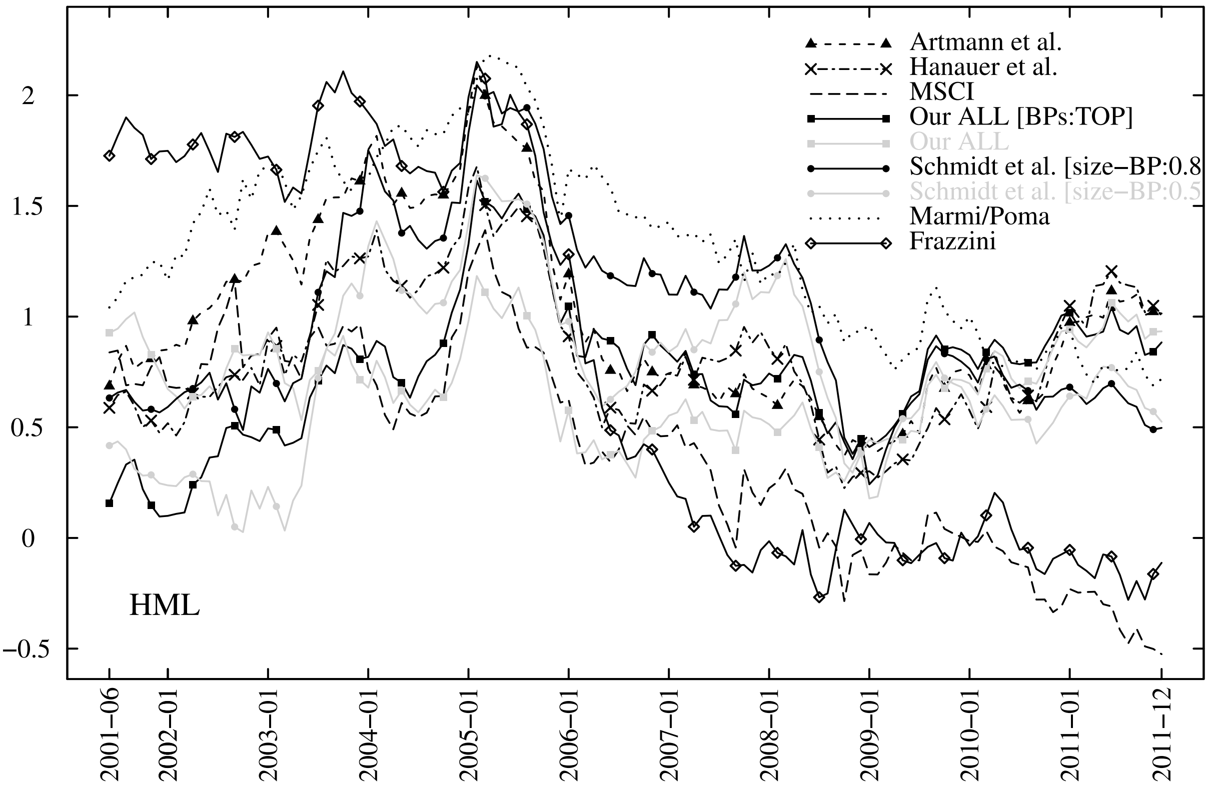
In the HML figure (Figure 3), the rolling means differ by 1.5%-points at the beginning and at the end. The HML time series based on MSCI indices and Frazzini's time series are much lower than the other seven at the end. The seven other means differ at the end by only 0.5%-points. Hence, here, only 7 out of 9 time series converge over time. It can also be seen that a value effect exists over the entire time period we look at, and it is the most pronounced from 1998 to 2005.

The correlations between the HML time series are even lower than the correlations between the SMB time series: The lowest R^2 between any pair is 0.04, and the highest is only 0.49. The time series of Marmi/Poma and the time series based on MSCI indices are practically uncorrelated with all others. We believe that the low R^2 values are mainly caused by the treatment of dual-class firms (see Section 3.1.5) and the quality of the underlying databases. To calculate an HML factor time series, book values of equities are needed; some of the underlying databases may be more complete than others or may have different values.

The HML time series also show that the choice of breakpoints matters. The means of our two ALL series with different breakpoints differ considerably, as do the means of the two series of Schmidt et al.

Figure 3: Rolling Means of Nine HML Time Series

Each point in this graph is based on the prior 60 months, starting in 06/2001 (including the time period of 07/1996 to 06/2001).



4.4 The WML Time Series

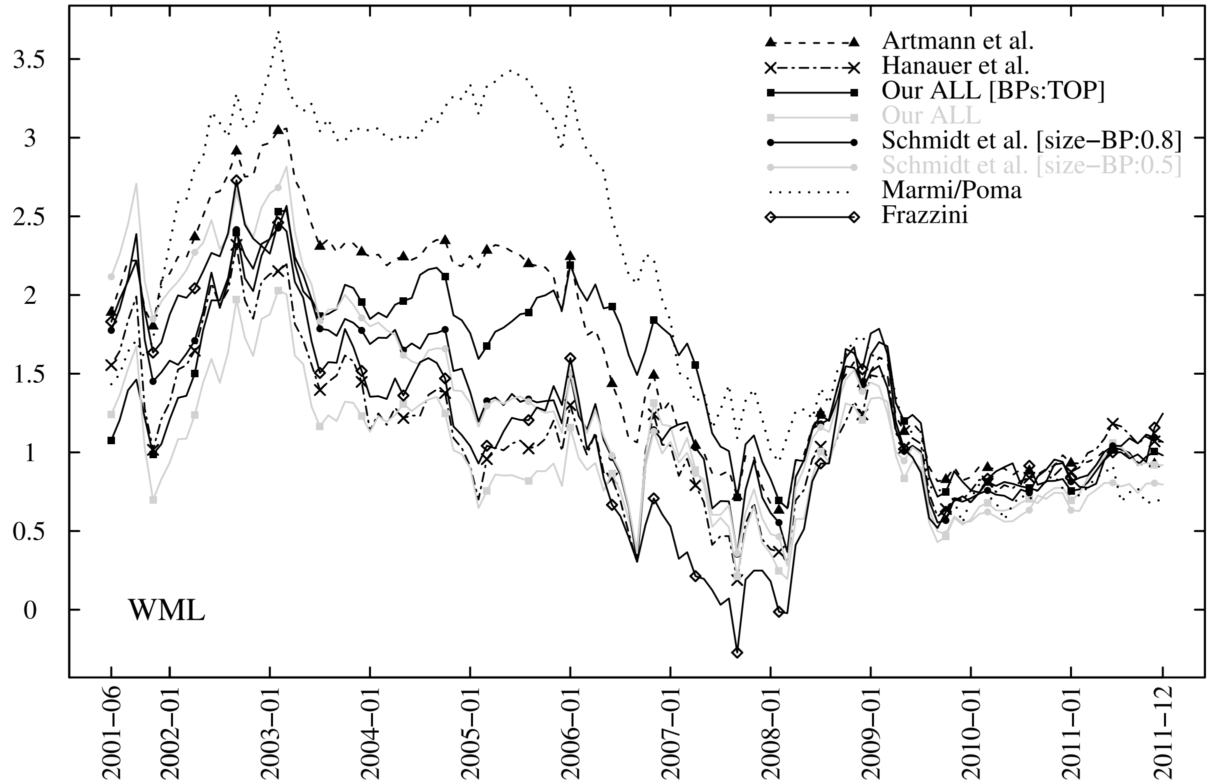
The WML time series are more similar to each other than the SMB and HML time series. All means are higher than 1% per month (see Panel D of Table 3), which is considerably higher than the means of the other factor time series. The lowest mean is 1.05% (our ALL), and the second lowest is 1.19% (Hanauer et al.). The highest mean is 1.60% (Marmi/Poma), and the second highest is 1.44% (Artmann et al.). None of the means is significantly different from the others. Again, the mean of Frazzini's WML factor changes considerably with the updated time series (1.24% vs. 1.59%); this time the mean again moves away from the others.

Most impressive are the rolling means (Figure 4). In the first years, the means differ from each other by up to 1%-point, while during the last three years, they are nearly identical. We have seen a similar but less pronounced general pattern in the figures for the market, the SMB and the HML time series. This we interpret as strong evidence for our conclusion that a major cause of the differences between the factor time series is the quality of the underlying databases.

The correlation coefficients confirm the high similarity between the WML time series: The lowest R^2 between any pair of the series is 0.32 (Frazzini and Marmi/Poma), and the highest is 0.83 (Hanauer et al. and Schmidt et al., see Panel D of Table 4).

Figure 4: Rolling Means of Eight WML Time Series

Each point in this graph is based on the prior 60 months, starting in 06/2001 (including the time period of 07/1996 to 06/2001).



5. Two Applications

The previous section documents considerable differences between some of the factor time series. In several cases, the differences between the means are statistically significant, and some factor time series are practically uncorrelated with their counterparts. This suggests that the 'quality' of the factor sets differs. This may matter in some applications and in turn affect the results and inferences drawn from the data.

In this section, we first analyze the performance of 41 mutual funds that focus on German stocks and then analyze how well the different factor data sets can explain the returns on 16 size/book-to-market and 16 size/momentum portfolios. We estimate one-factor and four-factor regressions.[17] The one factor regression only uses the excess return on the market, and the four-factor regression is given by

$$R_{i,t} - R_{k,t}^{f} = \alpha_{i,k} + b_{i,k}\left(R_{k,t}^{M} - R_{k,t}^{f}\right) + s_{i,k}SMB_{k,t} + h_{i,k}HML_{k,t} + w_{i,k}WML_{k,t} + \varepsilon_{i,k,t}, \qquad (1)$$

where $R_{i,t}$ is the return of fund i, $R_{k,t}^{f}$ the risk free rate and $R_{k,t}^{M}$ the return on the market provided by factor data set k in month t. The time series for the factors provided by factor data set k in month t are given by $SMB_{k,t}$, $HML_{k,t}$ and $WML_{k,t}$. The intercept, $\alpha_{i,k}$, and the factor loadings $b_{i,k}$, $s_{i,k}$, $h_{i,k}$ and $w_{i,k}$ are the estimates from time series regressions for fund i under factor data set k.

In both applications, we also check whether four-factor models based on the various data sets improve a simple one-factor model based on well-established indices for the German market. In the analysis of the two sets of 16 portfolios, this is nearly always the case. In the analysis of mutual funds, only two of the six four-factor data sets we look at have a higher mean adjusted R^2 than one-factor models based on either the CDAX or the MSCI Germany. Because of this important finding, one-factor models play an important part in the mutual fund analysis but not in the analysis of the 16 portfolios.

5.1 Mutual Fund Performance

We use a sample of 41 mutual funds that invest in German stocks that have been in operation from 07/1996 to 08/2011.[18] Thus, we only consider mutual funds that existed over the whole time period. This introduces a survivorship bias but satisfies the purpose of this application: to demonstrate that the use of different four-factor data sets for Germany can lead to different inferences drawn from the data. We estimate the regressions for the 41 funds individually as well as for an umbrella fund (fund of funds). The return on the umbrella fund is the market value-weight return (market value as of December of the previous year) of the individual fund returns.

The left-hand side of Table 5 shows the results for the one-factor regressions based on the market factors of the various providers as well as on the CDAX, the MSCI Germany, and French's time series for Germany. Presented are the means of the annualized alphas and the means of the R^2 of the 41 regressions we conduct for each factor set (or index). Also shown is the number of individual funds that have a significant negative or positive alpha on at least a 10% level. We obtain for all factor sets, except for Frazzini (1.02) and Marmi/Poma (0.60), a negative mean alpha, which is in line with our expectations. In comparison to the low mean

[17] The one factor version of the model goes back to Jensen (1968) and Black/Jensen/Scholes (1972) [BJS].

[18] The mutual fund data is precisely explained in Lehmann (2013). Our sample builds on his final sample of 128 funds. It is important to note that the mutual fund data is from the Bundesverband Investment und Asset Management e.V. (BVI), and the returns of funds thus contain the corporate income tax credit (see Section 3.1.7). To be correct, only benchmark data that include the corporate income tax credit should be used to evaluate the performance of these funds. However, because we only compare the different factor sets and none of the other suppliers provide a factor set with the tax credit, we ignore this point and use our time series without the corporate income tax credit.

alphas by Artmann et al. (-2.07) and Hanauer et al. (-1.92), the difference is roughly three percent per annum, a huge difference in the context of a performance evaluation. The mean R^2 is higher than 0.8 for most market proxies, and for Marmi/Poma, it is only 0.45. It is highest for the CDAX and for Artmann et al.'s market time series, which is the CDAX after 2004. The reason for the high mean R^2 for the MSCI Germany and CDAX should be related to the index supplier's approach of weighting stocks by their free-float market capitalization rather than by their total market capitalization (see Stehle/Schmidt (2015) for details). Based on Artmann et al., the ratio of statistically significant negative to positive fund alphas is 16:0. We attribute this to the high mean return of the market proxy they use until 2004, the DAFOX, which we think is mainly due to its error in 1998 and the non-inclusion of the former Neuer Markt (see also Section 4.1).[19] Based on Frazzini, on the other hand, the ratio is 0:2, which is obviously related to its low mean market return.

Table 5: Factor Data Sets Applied to Mutual Funds

$$R_{i,t} - R^f_{k,t} = \alpha_{i,k} + b_{i,k}\left(R^M_{k,t} - R^f_{k,t}\right) + s_{i,k}SMB_{k,t} + h_{i,k}HML_{k,t} + w_{i,k}WML_{k,t} + \varepsilon_{i,k,t}$$

This table shows results from one-factor and four-factor regressions applied to 41 mutual funds that invest in German stocks as well as for a fund of funds. The results are shown for different factor sets for the time period of 07/1996 to 08/2011 (182 month). We use the factor set by Schmidt et al. with size breakpoint 0.8 and our factor set 'ALL' with breakpoints from the top segment without the tax credit. "+" ("-") indicates the number of funds that have a positive (negative) and statistically significant alpha on at least a 10% level. Alphas are annualized (multiplied by 12) and given in percentage. The coefficients for b are tested against one. Asterisks ***/**/* show significance at the 1/5/10% level. Test statistics are based on Newey-West standard errors.

	One-Factor			Four-Factor								
	41 individual Funds			41 individual Funds			Fund of Funds					
Provider/ Factor Set k	Mean of annu-alized α	# of stat. sign. α [+ / -]	Mean of R^2	Mean of annu-alized α	# of stat. sign. α + / -	Mean of Adj. R^2	α	b	s	h	w	Adj. R^2
Artmann et al.	-2.07	0 / 16	0.89	-1.02	1 / 8	0.90	-1.44	1.06***	0.01	0.04	-0.07**	0.96
Frazzini	1.02	2 / 0	0.85	1.57	5 / 1	0.87	1.52	1.03	-0.09*	0.21***	-0.15***	0.92
Hanauer et al.	-1.92	0 / 6	0.73	-1.07	0 / 4	0.76	-1.38	1.02	0.19**	0.20***	-0.09*	0.80
Marmi/Poma	0.60	0 / 0	0.45	-0.13	0 / 0	0.48	-0.59	1.10	0.20	0.25*	-0.05	0.50
Our: ALL	-0.55	0 / 4	0.88	0.19	2 / 2	0.90	0.17	1.07**	0.02	0.11***	-0.10***	0.95
Schmidt et al.	-0.27	0 / 1	0.77	0.33	0 / 1	0.79	0.31	1.07	0.11	0.11*	-0.08*	0.83
CDAX	-0.10	0 / 3	0.89									
French	-0.75	0 / 5	0.87									
MSCI	-0.41	0 / 4	0.88									

The middle to right-hand side of Table 5 shows the results for the four-factor regressions. Measured by the mean adjusted R^2, the four-factor regressions improve their one-factor counterparts in our context only marginally. The result based on our four-factor data (ALL), e.g.,

19 Bessler et al. (2009), in their analysis of the conditional performance of German equity mutual funds note the following: "Again, we observe that the DAFOX index produces lower alphas than the other indexes […]".

has a mean adjusted R^2 of 0.90; for the one-factor counterpart we obtain 0.89. An important result is that all except two four-factor data sets (our ALL and Artmann et al.) have a lower mean adjusted R^2 than the one-factor regressions based on either the CDAX or the MSCI Germany. Again the ratio of statistically significant negative to positive fund alphas differs considerably across the factor sets: For Artmann et al., it is 8:1; for Frazzini, it is 1:5, and the others are in between. The high positive mean alpha of Frazzini's factor set (1.57) is again out of line compared to the other providers. Its relatively high mean adj. R^2 reflects the high correlation of its excess return with the best market proxies. The adj. R^2 for the combined value-weight portfolio of the 41 funds (fund of funds) are all a bit higher. They have the same patterns across the different factor sets as the mean adj. R^2 based on the individual funds. Again, large differences between the estimated alphas occur, ranging from -1.44 (Artmann et al.) to 1.52 (Frazzini). But none of the alphas is statistically significant. Some factor sets result in statistically significant factor loadings, while others do not. However, all factor sets agree on the following: The funds, taken together, have a mean beta that is higher than one, their factor loading on SMB is positive (here, Frazzini would disagree), their factor loading on HML is positive and that of WML is negative.

The exploratory analysis of the 41 mutual funds that focus on German stocks clearly demonstrates that at present, a researcher must be very careful when analyzing mutual fund performance in Germany with the four-factor model. Different factor sets may result in very different estimates for the abnormal performance of individual funds and for their average abnormal performance. In the short run, the only way to reach reliable conclusions about the performance of German mutual funds based on a three- or four-factor model seems to be the use of alternative factor sets in the analysis to get a feeling for the robustness of the results. However, a larger data set and/or a longer time horizon may be better suited to identify the quality of a factor set.

For an analysis of mutual funds, the most important aspect of a factor set seems to be the quality of the included market time series. The factors HML, SMB and WML improve the R^2 only marginally. By using a one-factor model based on a well-established market index, a mutual fund evaluator can avoid uncertainty about the quality of a specific factor set.

5.2 Size/Book-to-Market and Size/Momentum Portfolios

In our second application, we analyze how well the alternative factor sets are able to explain the cross-sectional dispersion of the average returns of 4x4 size/book-to-market and 4x4 size/momentum portfolios. In our analysis of mutual funds, the market factor plays an important role because most of the fund portfolios are very similar to the market portfolio. The portfolios in the two sets, on the other hand, differ much more with respect to the characteristics proxied by the other three factors. Hence, the other factors should play a much more important role in this application than in the fund analysis.

We first sort all non-financial firm observations from the top segment according to size and then within each size quartile by book-to-market or momentum (dependent sort)[20] and allocate the stocks from the middle segment and the former Neuer Markt to the portfolios. The portfolios are value-weight, and the sorting is updated each year end of June. We then regress the excess return of these portfolios on the different Fama/French factor sets. Note that this procedure favors our factor sets, as the test assets and the factors are based on the same database. It favors our factor set ALL [BP Top] most because the portfolios are also constructed with breakpoints from the top segment. This factor set has the highest mean adj. R^2 in all analyses we report in Table 6.

For each factor set, we test the null hypothesis that all 16 alphas are jointly zero by employing the Gibbons/Ross/Shanken (1989) test (GRS-test). The GRS-test in this context is a major improvement over the procedure suggested by BJS. It is based on the same assumptions as the BJS test procedure: stable factor loadings, homoscedastic errors and the assumption that the variance-covariance of the residuals is stable over time. Because these assumptions may be violated to some extent, the p-values of the tests may be biased downwards, especially when the test covers a long time period.

Table 6: Factor Data Sets Applied to Value-Weight Size/Book-to-Market and Size/Momentum Portfolios

$$R_{i,t} - R^f_{k,t} = \alpha_{i,k} + b_{i,k}\left(R^M_{k,t} - R^f_{k,t}\right) + s_{i,k}SMB_{k,t} + h_{i,k}HML_{k,t} + w_{i,k}WML_{k,t} + \varepsilon_{i,k,t}$$

This table shows means of (absolute) alphas and adjusted R^2 obtained from four-factor regressions applied to 16 size/book-to-market and 16 size/momentum portfolios plus corresponding GRS-test statistics (p-values). We first sort all non-financial firm observations from the top segment according to size and then within each size quartile by book-to-market or momentum (dependent sort) and allocate the stocks from the middle segment and the former Neuer Markt to the portfolios. The sorting is updated each year end of June. The results are shown for different factor sets for the time period of 07/1996 to 12/2011 (186 months). We use the factor set by Schmidt et al. with size breakpoint 0.8 and our factor set 'ALL' with breakpoints from the top segment without the tax credit. Alpha's are on a monthly basis, given in percentage form. Asterisks ***/**/* show significance for the GRS-test at the 1/5/10% level.

	16 Size/Book-to-Market Portfolios				16 Size/Momentum Portfolios			
Provider/ Factor Set k	Mean of $\lvert\alpha\rvert$	Mean of α	Mean of Adj. R^2	GRS-test (p-values)	Mean of $\lvert\alpha\rvert$	Mean of α	Mean of Adj. R^2	GRS-test (p-values)
Artmann et al.	0.27	0.23	0.69	0.24	0.37 ***	0.19	0.70	0.00
Frazzini	0.41 **	0.40	0.62	0.04	0.57 ***	0.34	0.64	0.00
Hanauer et al.	0.27	0.17	0.67	0.29	0.44 ***	0.10	0.70	0.00
Marmi/Poma	0.26	0.13	0.52	0.53	0.47 ***	0.04	0.53	0.00
Our: ALL	0.27 **	0.19	0.73	0.05	0.46 ***	0.15	0.75	0.00
Schmidt et al.	0.28	0.07	0.67	0.30	0.43 ***	-0.00	0.69	0.00

Table 6 shows the results for the 16 size/book-to-market and the 16 size/momentum portfolios. Note that we report in addition to the mean alpha the mean of the absolute alphas because the latter is an important input factor in the GRS-test. The four-factor regressions based

[20] For an independent sort, we typically do not have a sufficient number of stocks, especially in the extreme portfolios.

on the various factor sets all have mean adjusted R^2s, which are considerably higher than their one factor counterparts. As a consequence, we only report the full details for the four-factor regressions.

For the 16 size/book-to-market portfolios, the GRS-tests lead to very different rejection rates (*p*-values) for the different factor sets, ranging from 0.04 to 0.53. For two factor sets (our ALL, Frazzini), we can reject the null hypothesis that all 16 alphas are jointly zero (on at least a 10% level). Frazzini's data produces alphas that are on average twice as high as the alphas based on the other factor sets. The main reason for the rejection of the null seems to be the downward biased market proxy. The mean adjusted R^2 based on our data (0.73) is higher than that of Frazzini (0.62). Here, the higher power seems to be the main reason for the rejection. The factor set by Marmi/Poma produces the lowest mean adjusted R^2 (0.52). Hence, the factor set's ability to explain the variation of the returns on the size/book-to-market portfolios is considerably lower than for the other factor sets.

In the analysis of the 16 size/momentum portfolios, all factor sets produce mean absolute alphas that are considerably higher than those of the size/book-to-market portfolios. The GRS-test produces for all factor data sets *p*-values that are essentially zero, rejecting the null that all 16 alphas are jointly equal to zero. The large pricing errors typically emerge among the extreme momentum portfolios (results not tabulated), less among the size dimension. Hence, the strong momentum returns do not fall within the prediction of the four-factor model. This is unexpected because the WML factor included in the factor model is supposed to capture the momentum returns. We suspect that the standard factor construction based on winner minus loser stocks with a 30/40/30 sorting is too conservative to capture the large average returns among the stocks with the strongest short-term return continuation. For example, a sorting based on 20/60/20 or even 10/80/10 may be an appropriate alternative.

However, while all factor data sets lead to the same conclusion based on the GRS-test statistics, considerable differences exists with respect to the individual portfolio alphas. Artmann et al. produces the lowest mean of absolute alphas (0.37), and Frazzini the highest mean of alphas (0.57).

6. Summary

All factor data sets for Germany that we look at cover at least the time period 07/1996 to 12/2011. For this time period, we compare the means of the monthly time series of market excess returns and the HML, SMB and WML time series. The mean of the market excess return time series provided by Hanauer et al. is nearly twice as high as that provided by Marmi/Poma and Frazzini. In some cases, the differences between the means are statistically significant. Considerable differences also exist between the means of the SMB and HML time series. For the SMB time series, we find the largest number of pair-wise means that are statistically significantly different from each other.

We also find that all correlations between the factor time series of Marmi/Poma and their counterparts are extremely low. In addition, the SMB and HML time series based on MSCI size and style indices, as well as the SMB and HML time series of Frazzini, show relatively low correlations (mostly well below 0.4) with the other supplier's time series. We also show that the differences between the means decrease considerably over time. This we interpret as strong evidence for our conclusion that the major cause of the differences is the quality of the underlying databases. There is reason to believe that the differences before 1996 are even larger than those we find for the years after 1996.

In two standard applications, we study to what extent the choice of a factor set affects the result of an empirical analysis. In the first application, we study the performance of 41 mutual funds that focus on German stocks. Our results reveal that all except two four-factor data sets (our ALL and Artmann et al.) have a lower mean adjusted R^2 than a one-factor model based on either the CDAX or the MSCI Germany. Hence, researchers should carefully consider whether to use a one-factor model based on a well-established market index or a four-factor model based on a data set whose quality is uncertain. As a consequence of the differences in the underlying data, the number and type of statistically significant alphas differ considerably among the factor data sets we look at.

In the second application, we look at 16 size/book-to market portfolios and at 16 size/momentum portfolios. We regress the excess return of these portfolios on the different factor sets and test the null hypothesis that all 16 alphas are jointly zero. For this hypothesis, we find considerable differences in the rejection rates (*p*-values) among the factor data sets when we look at the size/book-to-market portfolios.

Both applications reveal that some factor sets are more likely to create biased results (unusual high or low alphas) due to their systematically upward or downward biased factors. Other factor sets do not appropriately capture the variation in the left-hand side variable (unusually low R^2). Our analysis clearly demonstrates that researchers should choose the factor model and factor data carefully.

Appendix A: Construction of Fama/French Factors based on MSCI Indices

Using MSCI indices seems to be a convenient alternative to calculate Fama/French factors because the data for the relevant indices are available online. We obtain the "gross" (total) return time series in "local" currency and estimate the return on the market portfolio, SMB and HML factor portfolios based on the following indices. The return on the market is based on the MSCI Germany. The SMB factor is the difference between the returns on the MSCI Germany SMID Cap (small and mid caps) and the MSCI Germany Large Cap. For the HML factor, we use the MSCI Germany Value and MSCI Germany Growth indices. Unfortunately, MSCI does not provide a momentum index for Germany; only a European index seems to be available. It is important to note that the calculation of the growth and value indices are not comparable to the methodology suggested by Fama/French. For example, the value index by MSCI also takes forward-looking variables such as the "12-month forward earnings to price ratio" into account.[21]

Appendix B: Details of the Comparisons of the Factors (Extension of Section 4)

Economically Significant Differences

To identify large errors in the factors, we compute normalized time series (mean: zero, standard deviation: one) and calculate absolute differences between single data points (months). We normalize the time series because we want to compare the number of errors across factors. Two data points with an absolute difference larger than one are defined as a significant difference.[22] Again, to conserve space, we only include our factor set ALL with breakpoints from the top segment and the Schmidt et al. set with a size-breakpoint of 0.8 in the analysis.

Table A. 1 shows the results for the market excess return as well as for the SMB, HML and WML time series. Each part of the table (e.g., the first part that contains the results for the market excess return) is subdivided into two sections. The top one looks only at the differences within the group of the four 'major' providers that performed best in our preceding theoretical and empirical analysis (Artmann et al., Hanauer et al., Schmidt et al., and our ALL). The bottom section includes the other providers.

The results in Table A. 1 are fully in line with the results of our analyses of means and pairwise correlations:

- Between the time series for the market portfolio, relatively few large differences can be found, except for Marmi/Poma.
- The number of differences between the WML time series is a bit higher.
- Somewhat higher is the number of differences between the SMB time series.
- The differences are by far the largest between the HML time series.

[21] For details, see http://www.msci.com/products/indices/style/methodology.html (August 20, 2014).

[22] We also looked at the differences that are larger than two standard deviations (=2). These are less but have the same general pattern.

- The factor approximations based on the MSCI size and style indices for Germany and the factors of Marmi/Poma and Frazzini deviate often from the other SMB and HML series.

Table A. 1: Significant Differences Between the Factor Time Series

This table shows the number of significant differences between the factor time series of different providers. We use the factor set by Schmidt et al. with size breakpoint 0.8 and our factor set 'ALL' with breakpoints from the top segment without the tax credit. The construction of factors based on MSCI indices is described in Appendix A. The analysis is based on the time period of 1996/07 to 12/2011 (N=186). Each time series is normalized (mean: zero, standard deviation: one). A significant difference between two time series is an absolute difference of > 1 (one standard deviation). The last four columns show the number of months in which 1 or multiple (2-4) differences exist for a specific series. E.g., our market excess time series ("Our: ALL", Panel A) has two months in which it deviates significantly (by more than one standard deviation) from two other market excess time series.

Provider/ Factor Set	Mean number of significant differences	The significant differences are recorded toward				Months with one or multiple differences			
		Artmann et al.	Hanauer et al.	Our: ALL	Schmidt et al.	1	2	3	4
Panel A: R_m-R_f									
Artmann et al.	4.33	0	9	0	4	5	4	0	0
Hanauer et al.	5.33	9	0	7	0	6	5	0	0
Our: ALL	3.33	0	7	0	3	6	2	0	0
Schmidt et al.	2.33	4	0	3	0	3	2	0	0
CDAX	*2.00*	*0*	*5*	*0*	*3*	*4*	*2*	*0*	*0*
Frazzini	*4.00*	*2*	*7*	*0*	*7*	*6*	*5*	*0*	*0*
French	*2.25*	*0*	*5*	*1*	*3*	*7*	*1*	*0*	*0*
Marmi/Poma	*33.50*	*34*	*37*	*30*	*33*	*16*	*10*	*6*	*20*
MSCI	*3.00*	*0*	*6*	*1*	*5*	*6*	*3*	*0*	*0*
Panel B: SMB									
Artmann et al.	16.67	0	11	11	28	33	7	1	0
Hanauer et al.	16.33	11	0	16	22	30	8	1	0
Our: ALL	17.67	11	16	0	26	25	11	2	0
Schmidt et al.	25.33	28	22	26	0	29	7	11	0
Frazzini	*51.75*	*51*	*56*	*49*	*51*	*36*	*19*	*19*	*19*
Marmi/Poma	*64.00*	*62*	*64*	*72*	*58*	*33*	*24*	*21*	*28*
MSCI	*47.75*	*50*	*57*	*40*	*44*	*32*	*24*	*17*	*15*
Panel C: HML									
Artmann et al.	33.00	0	28	35	36	49	22	2	0
Hanauer et al.	37.00	28	0	36	47	49	19	8	0
Our: ALL	37.33	35	36	0	41	44	25	6	0
Schmidt et al.	41.33	36	47	41	0	44	22	12	0
Frazzini	*58.50*	*61*	*64*	*59*	*50*	*46*	*27*	*22*	*17*
Marmi/Poma	*62.00*	*54*	*72*	*62*	*60*	*38*	*37*	*16*	*22*
MSCI	*50.00*	*47*	*57*	*49*	*47*	*41*	*17*	*19*	*17*
Panel D: WML									
Artmann et al.	16.00	0	13	19	16	20	5	6	0
Hanauer et al.	8.33	13	0	7	5	16	3	1	0
Our: ALL	12.67	19	7	0	12	14	6	4	0
Schmidt et al.	11.00	16	5	12	0	17	5	2	0
Frazzini	*20.00*	*19*	*24*	*17*	*20*	*21*	*11*	*7*	*4*
Marmi/Poma	*35.75*	*24*	*38*	*46*	*35*	*26*	*16*	*11*	*13*

Within the group of the four ‘major’ factor providers, the SMB time series by Schmidt et al. exhibits a relatively high number of differences (76, divided by 3, a mean of 25.33) and has eleven data points (months) where the time series deviates significantly from all three other ‘major’ suppliers (see column “3“). This could be related to financial firms, which are included in the sample of Schmidt et al. but are excluded in the other three. Also worthwhile to note is that the results do not change considerably if we use the factor set of Schmidt et al. with a size breakpoint of 0.5 (73 significant differences).

The number of significant differences between the HML time series are about two times higher than that between the SMB series but without an outstanding number for an individual major series. The overall higher number of significant differences is most likely because the factor suppliers treat dual class firms differently (see Section 3.1.5) and the book values of equity data may differ between the different suppliers.

List of the Largest Differences

Table A. 2 looks at the months with the largest spreads between the (non-normalized) factors (based on Table A. 1). The absolute values of the spreads demonstrate that in applications with a small number of observations, e.g., event studies, the outcome may strongly depend on which factor set is used. Even if we only look at the four ‘best’ performing factor sets (Artmann et al., Hanauer et al., Schmidt et al., and our ALL with breakpoints from the top segment), considerable differences exist between the (non-normalized) factors in a large number of months. This could bias the results of studies based on these time series, especially if the samples are small. The largest spreads for a given month are:

- WML, 10/2001: 30.36% (Hanauer et al.: -40.71, our ALL [BPs: TOP]: -10.35);
- SMB, 11/1998: 11.69% (Hanauer et al.: 4.41, our ALL [BPs: TOP]: -7.28);
- HML, 10/2003: 11.54% (Artmann et al.: 1.93, Schmidt et al.: 13.47);
- R_m, 11/1998: 10.92% (Artmann et al.: 10.60, Hanauer et al.: -0.32).

Table A. 2: Months with Large Differences between the Factor Time Series

This table shows the months from Table A. 1 for which we find the largest spreads (maximum - minimum) between the factor time series of the four 'major' data providers. We use the factor set by Schmidt et al. with size breakpoint 0.8 and our factor set 'ALL' with breakpoints from the top segment without the tax credit. The construction of factors based on MSCI indices is described in Appendix A. The largest and smallest values are in grey.

	'Major' Data Providers/ Factor Set				Maximum Spread	*Other Time Series*				
Month	Artmann et al.	Hanauer et al.	Our: ALL	Schmidt et al.		*CDAX*	*Frazzini*	*French*	*Marmi/ Poma*	*MSCI*
Panel A: R_m-R_f										
1998-10	1.73	8.24	2.09	9.52	7.79	*3.48*	*1.78*	*2.73*	*-0.20*	*2.98*
1998-11	10.6	-0.32	8.91	0.17	10.92	*6.34*	*7.15*	*6.5*	*0.59*	*7.11*
1998-12	-0.69	5.29	-1.77	3.86	7.06	*-0.33*	*0.16*	*0.71*	*-1.77*	*0.71*
1999-11	4.35	11.23	4.92	6.58	6.88	*6.17*	*5.41*	*5.75*	*-1.65*	*7.07*
1999-12	14.95	11.68	15.65	8.64	7.01	*13.81*	*15.24*	*16.5*	*1.68*	*17.40*
2009-08	3.46	-5.30	0.03	-4.16	8.76	*3.46*	*2.30*	*0.04*	*2.67*	*2.88*
Panel B: SMB										
1998-10	-5.13	-9.77	-1.92	-6.31	7.85		*-4.26*		*-2.25*	*-1.36*
1998-11	-0.15	4.41	-7.28	2.34	11.69		*-0.51*		*1.54*	*-3.15*
1999-02	-0.60	3.73	3.74	7.68	8.28		*5.91*		*-1.85*	*4.40*
1999-03	-1.45	-6.44	1.32	-1.90	7.77		*4.42*		*-3.59*	*-1.00*
1999-04	-7.44	-5.01	-8.24	0.13	8.37		*-2.28*		*9.12*	*-4.82*
1999-11	-12.96	-14.30	-8.75	-6.13	8.17		*-8.28*		*-2.75*	*-2.03*
2002-07	1.88	2.27	2.83	9.79	7.91		*5.23*		*-8.54*	*1.49*
2003-01	-4.31	-5.79	-0.42	4.35	10.14		*0.45*		*1.02*	*0.16*
2003-04	0.52	-2.05	-1.40	-8.00	8.52		*-2.71*		*-8.70*	*-5.28*
Panel C: HML										
1998-11	-6.96	-3.14	2.40	-0.53	9.36		*4.03*		*2.19*	*1.98*
1999-01	-11.20	-3.73	-0.15	-11.04	11.05		*4.64*		*-1.27*	*10.42*
1999-03	9.65	8.56	-0.63	2.42	10.28		*5.54*		*0.55*	*6.40*
2000-02	-11.15	-4.49	-15.95	-10.19	11.46		*-9.49*		*-8.11*	*-3.85*
2000-11	19.23	9.33	14.54	13.36	9.90		*11.27*		*10.70*	*7.49*
2003-04	-1.67	7.58	-1.87	6.97	9.44		*0.91*		*-6.01*	*1.62*
2003-10	1.93	3.80	4.28	13.47	11.54		*2.56*		*0.14*	*1.18*
2006-04	0.66	-8.05	1.37	-1.06	9.42		*-3.16*		*3.60*	*0.98*
2009-07	-2.47	6.94	1.51	1.96	9.41		*3.97*		*1.03*	*0.79*
Panel D: WML										
2000-01	-3.88	6.97	7.80	8.52	12.40		*7.63*		*-8.72*	
2000-02	1.83	10.92	14.72	8.72	12.89		*7.04*		*3.55*	
2001-06	14.03	1.65	-0.43	8.46	14.46		*11.70*		*18.76*	
2001-09	5.41	10.03	8.54	19.64	14.23		*13.23*		*9.41*	
2001-10	-15.36	-40.71	-10.35	-37.54	30.36		*-14.77*		*-6.12*	
2001-12	16.79	14.22	5.64	6.15	11.15		*7.33*		*16.69*	
2002-02	9.23	10.60	8.78	-1.96	12.55		*10.42*		*15.13*	
2004-01	5.88	-3.29	1.65	8.50	11.79		*5.25*		*8.03*	

Appendix C: Recommendations to Users of German Factor Data Sets

We do not recommend using the German factor set provided by Marmi/Poma. Additionally, the original factor set by Frazzini gives the impression that it cannot compete with the other providers. It produces the most unrealistic results in our comparison based on 41 mutual funds: In the full time period that we observe, the mean alpha is 1.57% per year, and all other factor series except one produce negative mean alphas. The HML time series based on MSCI indices differs considerably from the other HML time series, which is not surprising, as the MSCI value and growth indices are constructed in a very different way.

The factor set by Artmann et al. is by construction and the underlying data very similar to our factor set ALL. However, Artmann et al. include the DAFOX as a proxy for the market, which is problematic because of the DAFOX error in 1998. To users, we suggest switching from the DAFOX to the CDAX after the official start of the latter in 1993. An additional weakness of the factor set by Artmann et al. is that they include the successful firms of the middle segment of the FSE in their calculations of SMB, HML and WML but not the unsuccessful ones.

We also do not recommend using the factor data provided by Schmidt et al. before 1990. Before 1990, Datastream in combination with Worldscope does not cover the German market correctly and has many weaknesses (see Brückner (2013)). After 1996, Schmidt et al. include considerably more stocks in their factor calculation than all other providers. This seems to be related to the inclusion of a large number of stocks from the lowest segment, which we think is not beneficial. It may suit some but probably not all users. Nevertheless, for most users, their series with a size breakpoint of 0.8 seems to be much more appropriate than the one with 0.5.

Hanauer et al., who also use Datastream and Worldscope data, made a wise decision to start in 1996. However, the exclusion of financials from their market time series is unusual; as a consequence, it has a much higher mean return than the proxies used by other providers. We recommend that users replace Hanauer et al.'s market time series with the CDAX. The proxy for the market portfolio offered by French is fully in line with the CDAX, the MSCI Germany, and our time series.

We recommend our factor sets because we offer a choice with respect to market segments and breakpoints. To users whose data to be analyzed consists mainly of stocks listed in the top segment of the FSE, we recommend the factor set TOP. To users whose basic data includes the former Neuer Markt, we recommend the factor set ALL with breakpoints from the top segment. Another reason that speaks for our factor sets is that we have compared our underlying databases with the other two major databases on the German stock market and have checked all major deviations carefully.

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IV. Trading Strategies Based on Past Returns – Evidence from Germany

Trading Strategies Based on Past Returns – Evidence from Germany*

Martin H. Schmidt‡

Abstract

Among the various strategies studied, only momentum investing appears to earn persistently non-zero returns. Over the total time period from 1965 to 2014, the classical momentum strategy based on performance over the past two to twelve months earned an average return of 1.57% per month (excluding microcap stocks and value-weight returns). In the most recent ten-year time period, it has been even larger: 2.27%, which is much larger than in the U.S. However, the profitability net of transaction costs appears weak because the strategy involves trading in disproportionately small stocks with high transaction costs, especially observed for the loser portfolio. A strategy that only concentrates on the winner portfolio and thus avoids potential problems associated with (short) selling the costly loser portfolio appears to earn strong and persistently abnormal profits, even after transaction costs have been taken into account.

Keywords: momentum, stock reversal, contrarian, transaction costs, predictability
JEL Classification: G11, G12

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1. Introduction

The relation between past returns and the cross-section of expected returns has been studied extensively. Different strategies that buy and/or sell stocks based on their past returns over diverging short-, intermediate-, and long-term horizons have emerged. Contrarian strategies, that is, a long position in past losers and a short position in past winners,[1] typically try to exploit the long-term (De Bondt/Thaler (1985, 1987) or the short-term (Jegadeesh (1990), Lehmann (1990)) reversal of stock returns. Momentum strategies (Jegadeesh/Titman (1993)), that is, a long position in past winners and a short position in past losers, bet on intermediate-term return continuation. Seasonality in the cross-section of stock returns, such as the predictability in the historical same-calendar month (Heston/Sadka (2008)), is also documented.[2]

There are numerous studies that have improved and specified some of the strategies. Also, more recent studies challenge the results from earlier work and have produced contrasting results (see the literature review in Section 2). However, most studies have so far focused on the U.S. stock market. Unfortunately, less is known for other capital markets. This is particularly precarious because the patterns found for U.S. stocks are not necessarily identical in other stock markets.[3] Concerns especially arise from data snooping (Lo/MacKinlay (1990b)). This highlights the need to study international capital markets and to provide *out-of-sample* tests to increase our confidence in the reliability of the results.

There are several studies that examine the returns of specific strategies in international capital markets. What they have in common is a broad analysis of a selected pattern, without going into detail for a specific stock market (see Section 2). The institutional differences of the included countries are also typically not taken into account. This, however, is reasonable because available data, resources, and most likely space, naturally limit further investigation.

I provide evidence on how various contrarian, momentum, and seasonality strategies performed in the German stock market from 1965 to 2014.[4] My focus on the German stock market offers the opportunity to study a non-U.S. stock market in the same depth as the U.S. stock market is investigated. In addition, joint analysis of various strategies under the same methodology allows for direct comparisons of returns and patterns, which is beyond most existing studies.

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1 In relation to the rest of the stock universe, this is, in the cross-section. This implies that in bear markets past winners could even have negative past returns but are better off in relation to others. Asness/Frazzini/Israel/Moskowitz (2014) discuss this in detail.

2 Note the difference to seasonalities in stock markets such as the weekend-effect, turn-of-the month effect, January effect, etc., see Rozeff/Kinney (1976), French (1980), Keim (1983), among many others and also see Schwert (2003) for a review. These strategies are not investigated in this paper.

3 An example is the classical momentum anomaly that cannot be found in some Asian countries (Hameed/Kusnadi (2002)), notably Japan (Liu/Lee (2001), Chui/Titman/Wei (2003), Griffin/Ji/Martin (2005)).

4 Common German synonyms for momentum are ‘relative Stärke’, ‘Kontinuitätseffekt‘, ‘zyklische Handelsstrategie‘. Common German synonyms for contrarian strategies (stock reversal) are ‘antizyklische Handelsstrategie‘, ‘Gewinner-Verlierer-Effekt‘.

This paper differs from existing German studies in the following aspects: The studies that evaluate momentum and contrarian strategies based only on German data typically cover a short time period (e.g., Stock (1990): 16 years, Külpmann (2004): 18 years), while this paper is based on sixty years of data. Also, the commonly used procedure is to calculate buy-and-hold (abnormal) returns, especially in the older studies that focus on long-term contrarian strategies (e.g., Sattler (1994), Daske (2002)). Here, I apply the present standard procedure used in the U.S. and calculate a time series of monthly (calendar time) portfolio returns, which has recently been adapted by a few German studies on momentum (Glaser/Weber (2003), Bohl/Czaja/Kaufmann (2015)). To my knowledge, none of the existing German studies applies value-weighting in their portfolio formation. This may be important when asking whether the strategies are accessible to investors with regards to transaction costs, liquidity, and other micro structure issues. I apply both procedures – equal-weight and value-weight returns – throughout this paper. A few papers (e.g. Baltzer/Jank/Smajlbegovic (2015)) do not distinguish between market segments and, as a result, most likely include stocks listed in the lowest segment or explicitly include stocks from the lowest segment (Meyer (1995)). Stehle/Schmidt (2015) recommend excluding these very small and illiquid stocks from an empirical study due to documented criminal activity, weak investors protection, and regulation. In addition, the selection of an adequate sample of stocks, especially with respect to small stocks, is very important when analyzing the German stock market. My results show that several strategies heavily rely on small stocks, which makes these strategies difficult to implement. A minor point is that a few studies (e.g., Glaser/Weber (2003), Baltzer et al. (2015)) do not skip the very last month (t-1) when forming portfolios for momentum strategies, which is the standard procedure for the U.S., due to short-term stock reversal.

My results are as follows: Among the studied strategies, only momentum produces high and persistent non-zero returns. The returns of long-term contrarian strategies are typically small and statistically insignificant. This result is different from the conclusions found in the German literature (e.g., Stock (1990), Schiereck/Weber (1995), Külpmann (2004)). I attribute the diverging results to the use of calendar-time returns instead of buy-and-hold returns and an insufficient treatment of microcap stocks. The result of small and statistically insignificant (raw) returns of long-term contrarian strategies is also different from the U.S. – only on a risk-adjusted basis do these strategies have returns that are indistinguishable from zero (Fama/French (1996)). The returns of short-term contrarian strategies are high but depend on microcap stocks, which is consistent with the majority of U.S. evidence. For the seasonality pattern reported by Heston/Sadka (2008), I can only find evidence until 2004 in Germany. For the last ten years, the returns are essentially zero and insignificant. Here, I conclude that the anomalous returns to this strategy disappeared soon after it was discovered.

Consistent with the evidence presented by Gong/Liu/Liu (2015) for the U.S., I find that a momentum strategy based on performance over the past three to twelve months (3-12 momentum strategy) produces the largest returns for Germany. Over the total time period from 1965 to 2014, the long-short portfolio (long in past winners, short in past losers) of this strategy earned an average raw return of 1.48% per month (excluding microcap stocks and value-weight returns), which cannot be explained by the Fama/French (1993) three-factor model. The sub-period with the largest average return is found in the most recent time period (2005–2014): 2.97% per month, which is much larger than in the U.S.

I add to the results by Glaser/Weber (2003) by showing that momentum relies disproportionately on small stocks when investing in German stocks. The average market capitalization represented by the winner portfolio is remarkably small, though even smaller are the stocks in the loser portfolio. I show that this has implications for the profitability of such strategies because of the higher transaction costs associated with these stocks. The monthly transaction costs estimates for the 3-12 momentum strategy based on actual turnover for the winner portfolio is about 0.33% and 0.53% for the loser portfolio (based on a sample excluding microcap stocks and value-weight returns). Generating trading profits net of transaction costs appears difficult, especially in light of the conservative transaction costs estimates, which *only* include the bid-ask spread.[5] However, because the majority of momentum profits arise from the winner portfolio, a strategy that only invests in past winners and thus avoids potential problems with (short) selling the costly loser portfolio appears to earn strong positive average returns, even after transaction costs.

This paper is organized as follows: Section 2 reviews the literature. Section 3 describes the data and sample selection. In Section 4, the most promising strategies are selected based on Fama/MacBeth cross-sectional regressions of individual future stock returns on their past returns. This section also describes how portfolios are formed. The raw and risk-adjusted returns of all strategies are evaluated in Section 5. The following Section 6 examines momentum in greater detail. The last Section 7 contains concluding remarks.

2. Literature Review

This section briefly reviews the U.S. and multi-country studies that include Germany in their analyses of momentum, contrarian, and/or seasonality strategies. It also includes a review of studies that focus on German stocks,[6] as well as a discussion of the change in methodology.

2.1 Studies with U.S. Data

That past returns contain information about expected returns has been studied extensively for the U.S. stock market by a large number of papers.[7] Different strategies have emerged that buy and/or (short) sell stocks based on their past returns over diverging short-, intermediate-,

[5] I use transaction costs and bid-ask spreads interchangeable in awareness that transaction costs involve more than only the bid-ask spread, see Section 6.3 for details.

[6] Studies that focus on reactions to price shocks, e.g. Atkins/Dyl (1990) for the U.S., Lobe/Rieks (2011) for Germany, are not discussed, although they are somewhat related especially to short-term contrarian strategies.

[7] A number of studies also find that some of the mentioned strategies, notably momentum, seem to be successful for other types of securities, see e.g., Okunev/White (2003), Erb/Harvey (2006), Asness/Moskowitz/Pedersen (2013).

and long-term horizons. De Bondt/Thaler (1985, 1987) find abnormal returns for contrarian strategies (buying past losers, selling past winners), which select stocks based on their performance over the past three to five years. Jegadeesh (1990) and Lehmann (1990) show evidence of short-term reversals and find that contrarian strategies generate abnormal profits when only the very recent stock returns, notable from the previous month, is the basis for portfolio formation. On the other hand, Jegadeesh/Titman (1993) find momentum strategies (buying past winners, selling past losers) are successful: stocks that have performed well (bad) over the previous 3-, 6-, 9- or 12-month tend to perform well (bad) in the future.[8] More recently, Heston/Sadka (2008) have found stock returns in the historical same-calendar month to be useful tools in predicting future returns.

The short-term reversal of stock returns has been of less interest in more recent years because Kaul/Nimalendran (1990), Jegadeesh/Titman (1995), Conrad/Gultekin/Kaul (1997), Avramov/Chordia/Goyal (2006), among others have found that measurement errors in prices minimize or even eliminate anomalous returns. Conrad et al. (1997) show that the profits of short-term contrarian strategies are caused by the bid-ask bounce in stock prices and are not exploitable. However, more recently De Groot/Huij/Zhou (2012) have found that when concentrating on only the largest stocks, abnormal profits net of transaction costs can be generated.

The returns of long-term contrarian strategies that try to exploit the long-term reversal of stock returns have also recently been of less interest. Zarowin (1990) argues that the results reported by De Bondt/Thaler (1985, 1987) are a manifestation of the size effect. Ball/Kothari/Shanken (1995) found microstructure effects to significantly reduce the returns of contrarian strategies. Probably most decisive was Fama/French (1996), who found that their three-factor model explains the returns of long-term contrarian investment strategies in the U.S.

Heston/Sadka (2008) attribute the fact that stocks "tend to have relatively high (or low) returns every year in the same calendar month" to seasonal variation in stock returns. They show that this pattern is not associated with earnings releases, dividends, and fiscal year-end, and is found in different industries, size classes and in every month. Keloharju/Linnainmaa/Nyberg (2015) argue that stocks do not repeat their return every twelve months but rather vary from calendar month to month. They document seasonality even in anomalies, stock market indices, and commodities.

The momentum anomaly, on the other hand, has been in the focus of research since the seminal paper by Jegadeesh/Titman (1993).[9] While many anomalies often disappear soon after their detection (Schwert (2003)), Jegadeesh/Titman (2001) confirm that even after the publication of their original paper, momentum remains profitable. Fama/French (2008) call momentum "the center-stage anomaly of recent years". However, the profits attributed to

[8] Moskowitz/Ooi/Pedersen (2012) document time series momentum, which is different to price momentum discussed here: The stock's individual performance relative to the rest of the universe (in the cross-section).

[9] See also Jegadeesh/Titman (2011) for a review of momentum literature.

momentum strategies in the U.S. have diminished in more recent periods (Hwang/Rubesam (2015)), and have even experienced a few extreme losses (Daniel/Moskowitz (2013)).[10]

There are various attempts to explain the momentum anomaly. Fama/French (1996) found their three-factor model cannot explain the returns of momentum strategies. Later, Grundy/Martin (2001) arrived at the same conclusion, based on time-varying factor exposures. Wang/Wu (2011) report that, on average, 34% of momentum returns can be explained by the three-factor model with a risk adjustment on the stock level. Chan/Jegadeesh/Lakonishok (1996) document a strong interaction between earnings and (price) momentum. Moskowitz/Grinblatt (1999) argue that a significant component of momentum profits stem from industry momentum rather than from stock-specific momentum. Chen/Stanzl/Watanabe (2002), Korajczyk/Sadka (2004) and Lesmond/Schill/Zhou (2004) find momentum profits are considerably lower when transaction costs are taken into account. Frazzini/Israel/Moskowitz (2012), on the other hand, argue that momentum strategies can be scaled and can generate strong net returns. There are also behavioral explanations that have been suggested (e.g., Barberis/Shleifer/Vishny (1998), Daniel/Hirshleifer/Subrahmanyam (1998), Hong/Stein (1999), Grinblatt/Han (2005), George/Hwang (2004)).

The profitability of momentum strategies in the cross-section has also been studied intensively. Hong/Lim/Stein (2000) find momentum to decrease with size and to be higher for stocks that have been covered by fewer analysts. However, Fama/French (2008) find momentum to be similar for both big and small stocks. Daniel/Titman (1999) find higher momentum profits for growth stocks than for value stocks, Lee/Swaminathan (2000) report higher profits for stocks with larger turnover. Avramov/Chordia/Jostova/Philipov (2007) find momentum profits only among firms with low credit ratings. Hillert/Jacobs/Müller (2014) find momentum profits to be more pronounced in firms with high media coverage.

There are also studies that have improved and specified some of the momentum strategies. Novy-Marx (2012) argues that a stock’s performance over the past seven to twelve months better predicts future returns than the traditional momentum sort based on past two to twelve months’ return. Gong et al. (2015), however, find no significant difference between the two strategies. Conversely, they found that momentum investing can be improved when the past three to twelve months of the stock’s history are used. Yao (2012) finds the superior performance of the seven to twelve months momentum reported by Novy-Marx (2012) caused by January seasonality.

2.2 Studies with Non-U.S. Data

The initial studies typically all focus on the U.S. stock market. An often-raised concern is whether the findings for the U.S. are reliable and generally valid in *all* stock markets, even in those that have different institutional environments.

[10] Barroso/Santa-Clara (2015) argue that these losses can be predicted and thus avoided.

The studies that examine certain momentum, contrarian, and seasonality strategies in international capital markets typically support those results found in U.S. stock returns. For example, Rouwenhorst (1998) finds momentum strategies to be profitable in twelve European countries. Griffin/Ji/Martin (2003) find large momentum profits internationally, which are almost unrelated to macroeconomic factors. Heston/Sadka (2010) examine the annual pattern found by Heston/Sadka (2008) for U.S. stocks in an international context, and finds similar results.

However, notable exceptions exist, especially for Asian countries. Liu/Lee (2001) find no momentum in Japan, Hameed/Kusnadi (2002) arrive at the same conclusion for six other Asian countries. Chui et al. (2010) later confirm this for many Asian and also a few non-Asian countries (e.g., Turkey, Argentina), and give behavioral explanations related to cultural differences.[11] Goyal/Wahal's (2015) study on momentum based on the sorting of past returns over seven to twelve versus two to twelve months in international stock markets finds no significant difference, except for the U.S.

2.3 Studies with German Data

Table 1 provides an overview of studies that have been conducted by using only German data. The studies are divided according to their focus on momentum and long- or short-run contrarian strategies.[12]

Stock (1990) was probably the first study to analyze the returns of long-term contrarian strategies in Germany. Over the time period from 1973 to 1989, he finds a long-term stock reversal for a sample of 41 large stocks. Subsequent papers that study winner-loser effects typically also find contrarian strategies to be profitable. Sattler (1994) finds past losers, but not winners, to have returns that are significantly different from the market after one year. Schiereck/Weber (1995) and Meyer (1995) find large buy-and-hold abnormal returns for a five-year formation and five-year holding period. Schiereck/De Bondt/Weber (1999) also study long-term contrarian strategies in Germany and conclude that "contrarian strategies […] appear to be profitable", although their mean BHAR of the long-short portfolio is typically statistically indistinguishable from zero for multiple holding periods. When using a four- and five-year period for portfolio formation, Daske (2002) usually finds abnormal returns after three, four, and five years, but not in the first and second year after portfolio formation. However, he reports that the returns of the long-run contrarian strategies disappear after controlling for risk. Külpmann (2004) reports for time horizons of three years or longer significant excess returns for a contrarian strategy.

Schiereck/Weber (1995) find significant abnormal returns for momentum strategies when sorting stocks based on their performance over the past three, six and, twelve months respectively. Bromann/Schiereck/Weber (1997) confirm the results and find momentum profits to be robust with respect to transaction costs, short-selling constraints, and illiquidity. Schiereck et

[11] See also Chui/Titman/Wei (2003) and Griffin/Ji/Martin (2005) for international evidence and exceptions.
[12] Because of the different methodologies applied I only include their general result and no specific numbers.

Table 1: German Literature Overview on Momentum and Contrarian Strategies

Author(s)	Data Source	Time Period Covered	Years	(Abnormal) Return Calculation	Market segment(s) / Sample	Weighting	Important Result(s)
Momentum							
Schiereck/Weber (1995)	KKMDB	1961-1991	30	CAR and BHAR	AM	EW	Significant abnormal returns when sorting stocks based on three to twelve months past performance
Bromann/Schiereck/Weber (1997)	KKMDB	1973-1993	20	BHAR	AM	EW	Momentum seems to be profitable even after controlling for transaction costs, short-selling constraints and illiquidity
Schiereck/De Bondt /Weber (1999)	KKMDB	1961-1991	30	BHAR	AM	EW	"Momentum and contrarian strategies both appear to be profitable."
August/Schiereck/ Weber (2000)	KKMDB	1973-1997	24	BHAR	AM	EW	Momentum strategies are profitable, even on a risk-adjusted basis
Glaser/ Weber (2003)	Datastream	1988-2001	13	Calendar Time	AM	EW	Large and persistent returns of momentum strategies, stronger in high turnover stocks and mainly driven by mid-cap stocks and
Bohl/Czaja/ Kaufmann (2015)	Datastream	1987-2012	25	Calendar Time	unknown	EW	"[…] momentum strategies perform generally well, but not during times of volatile market reversals."
Baltzer/Jank/Smajlbegovic (2015)	Datastream	2006-2012	7	Calendar Time	unknown	EW	"[…] the momentum strategy is highly profitable".
Long-Term Contrarian							
Stock (1990)	Westdt. Landesbank, BZ	1973-1989	16	CAR	AM[1]	EW	"Evidence on long-term overreaction is found."
Sattler (1994)	Stehle	1954-1991	37	BHAR	AM	EW	A significant loser anomaly in the German stock market, but not for winner
Meyer (1995)	KKMDB	1964-1990	26	BHAR	AM, GM, FV	EW	Abnormal returns for certain strategies, doubts that they survive because of transaction costs and short-selling constraints
Schiereck/Weber (1995)	KKMDB	1961-1991	30	CAR and BHAR	AM	EW	Significant abnormal returns for contrarian strategies
Schiereck/De Bondt /Weber (1999)	KKMDB	1961-1991	30	BHAR	AM	EW	"Momentum and contrarian strategies both appear to be profitable."
Daske (2002)	Stehle	1953-1995	42	BHAR	AM	EW	Based on risk-adjusted returns no significant abnormal returns for winner and loser stocks
Külpmann (2004)	KKMDB	1968-1986	18	BHAR	unknown	EW	"For time horizons of three years or longer I report excess returns for a contrarian strategy."
Short-Term Contrarian							
Bromann/Schiereck/Weber (1997)	KKMDB	1973-1993	20	BHAR	AM	EW	Short-term contrarian strategies have large returns; probably disappear after transaction costs

KKMDB=Karlsruher Kapitalmarktdatenbank, BZ=Börsen Zeitung, [1] Stocks accepted for option trading (N=41) al. (1999) and August/Schiereck/Weber (2000) also find momentum strategies to be profitable. Glaser/Weber (2003) report for a momentum strategy based on the past performance over the last twelve months and with rebalancing every three month an average monthly return of 1.07%. Similar to the U.S. study by Lee/Swaminathan (2000), they find that momentum strategies are more profitable among high-turnover stocks. In addition, Glaser/Weber (2003) find momentum to be mainly driven by medium-sized stocks and related to book-to-market and industry. A more recent study by Bohl et al. (2015) focuses on momentum crashes in Germany and finds momentum strategies to generally perform well, though they have their limits in volatile markets. Baltzer et al. (2015) find that foreign investors and financial institutions engage in momentum strategies in Germany but not private households.

To my knowledge, the only German study that reports returns of short-term contrarian strategies is Bromann et al. (1997), finding a monthly return of 1.19%, though they question the profitability once transaction costs have been considered.

2.4 The Change in Methodology

De Bondt/Thaler (1985, 1987) and most subsequent studies examine the profitability of long-term contrarian strategies by calculating average cumulative raw returns. Conrad/Kaul (1993) criticize this procedure (see also Ball et al. (1995) and Barber/Lyon (1997)). They show that the profitability of such strategies is upwardly biased, due to the methodological drawback of cumulating short-term (monthly) returns over long periods. Conrad/Kaul (1993) suggest calculating buy-and-hold (abnormal) returns (BHARs) instead of cumulative raw or abnormal returns.

The calculation of BHARs is a common procedure and can be found in many subsequent studies, including those focusing on the German stock market (see Table 1). However, Fama (1998) and Mitchell/Stafford (2000) have criticized the use of the BHAR methodology to measure long-term performance. They advocate calculating a time series of monthly (calendar time) portfolio returns. They argue that this methodology is less subjected to the bad-model problem – the unavailability of a perfect expected return proxy –, non-normality of returns (skewness), and correlation of returns across events that arise when the event window increases.

The calculation of a time series of monthly portfolio returns has become the standard procedure in most recent U.S. studies. In Germany, only the three most recent studies on momentum (Glaser/Weber (2003), Bohl et al. (2015), Baltzer et al. (2015), see Table 1) follow this approach.

2.5 Summary

As in other areas of Finance, research on trading strategies based on past returns is concentrated on the U.S. market. As a result, we typically know less about other capital markets, which can also be found for the German stock market.[13] While a vast amount of research has been conducted on momentum in U.S. stock returns, only a few papers have been published with their focus on Germany. The most recent knowledge on short- and long-term contrarian strategies in Germany is that they seem to generate abnormal returns, which is different from what is known for the U.S. stock market.

What the studies that examine the returns of certain momentum, contrarian, and seasonality strategies in international capital markets have in common is their broad analysis of a selected pattern, without going into the details for a specific stock market. This is reasonable because available data, resources, and most likely space naturally limit a paper. My focus on only the German stock market offers the opportunity to study a non-U.S. stock market in the same depth as the U.S. stock market is typically investigated.

Existing studies that have a focus on the German stock market and studies that include Germany as part of their multi-country study typically only cover a short time period (see Table 1). The commonly used procedure to calculate BHARs, especially in studies focusing on long-term contrarian strategies in Germany, requires a more sophisticated analysis of the patterns in German stock returns. In addition, studies that do not distinguish between stock market segments, which is difficult when Datastream data is used (Brückner (2012)), most likely include stocks that are listed in the lowest segment. Stehle/Schmidt (2015) recommend excluding these (very small and illiquid) stocks from an empirical study, due to documented criminal activity, weak investor's protection, and regulation. A minor point is that, e.g., Glaser/Weber (2003) and Baltzer et al. (2015) do not skip the very last month (t-1) when forming portfolios for momentum strategies, which is the standard procedure for the U.S. (due to short-term stock reversal). Finally, and most importantly, none of the existing German studies, to my knowledge, applies value-weighting in their portfolio formation. This may be important when asking whether the strategies are accessible to investors in the context of transaction costs, liquidity, and other microstructure issues.

3. Data and Sample Selection

In this paper, the stock market database of Richard Stehle is used, which is free from survivorship bias, includes all stock return components, and has been compared with other major data vendors. The data available for this study covers the years from 1955 to 2014 and thus includes sixty years of German stock market data. Included are all German common and preferred stocks with a listing in the top and middle segment, as well as stocks formally listed in the Neuer Markt of the Frankfurt Stock Exchange. Not included are stocks listed in the lowest segment (Open Market/Freiverkehr). All stock returns include the corporate income tax credit.

[13] If capital markets were fully integrated and operated identically, it may not be necessary to investigate patterns outside the U.S. because they can assume to be identical all over the world. However, the patterns found in the U.S. are not necessarily identical in international capital markets due to institutional, cultural, and other differences.

The database and many relevant details of the German stock market are described in Stehle/Schmidt (2015).

The inclusion of the Neuer Markt may have a considerable influence on the profitability and robustness of certain strategies because of its unique development. Stehle/Schmidt (2015) describe the rise and fall of this segment: The composite index of this former segment started at 500 (March 1997), increased to 8559 (March 2000), and finally ended at 403 points (March 2003). By the end of 2000, the Neuer Markt contained 282 stocks, which is remarkable for Germany since the top segment of the Frankfurt Stock Exchange contained *only* 411 stocks at the same time. The destination of these stocks is important for this study: they typically remained listed at the Frankfurt Stock Exchange for several years.[14]

The success of the strategies discussed in this paper has often been attributed to small firm and/or microstructure effects (see the literature review in Section 2). A strategy that is only found in small stocks may hardly be exploitable. Due to microstructure effects, such as illiquidity and high bid-ask spreads, the seeming profitability of a strategy may be illusory. In this context, Fama/French (2008) point out that microcap stocks can be particularly influential in equal-weight portfolios. Consequently, it seems reasonable to avoid a contamination of portfolios with very small stocks.

Fama/French (2008) classify stocks with a market capitalization that are below the 20th percentile of all NYSE stocks as microcap stocks. In the context of the German stock market, this approach may not be adequate due to the large variation in the number of tiny stocks through time (see below). An alternative is to set a minimum requirement in market capitalization. The U.S. Securities and Exchange Commission (SEC) defines stocks with a market capitalization of less than \$250 or \$300 million as "microcap stocks", and less than \$50 million as "nanocap stocks".[15] These definitions could be transferred to the German stock market but there are not as many stocks listed in the German market as there are in the U.S., and the U.S. stock market is considerably larger than the German market. The trade-off is between (1) a sufficient number of stocks available that are sorted into portfolios, and (2) a satisfactory limit in market capitalization to avoid to capture microstructure effects.

Figure 1 plots the total number of stocks (dotted line) available in the dataset between 1965[16] and 2014, along with the number of stocks with an inflation-adjusted market capitalization of less than €50 million (solid line) and less than €200 million (solid line with dots).[17] The share of stocks smaller than €50 million is about 30% in the sixties, then decreases to around 20% in the nineties. After the turn of the millennium, the share of stocks smaller than

[14] Excluding the Neuer Markt from the sample is not a satisfying alternative since after its closing in 2003 most of the stocks remained listed in the middle segment, which in 2007 was combined with the top segment to the new top segment. Also, the Neuer Markt represented a considerable amount (about 10%) of the total market capitalization of the Frankfurt Stock Exchange during the good years. See Stehle/Schmidt (2015) for details.

[15] http://www.sec.gov/investor/pubs/microcapstock.htm (April 15, 2015).

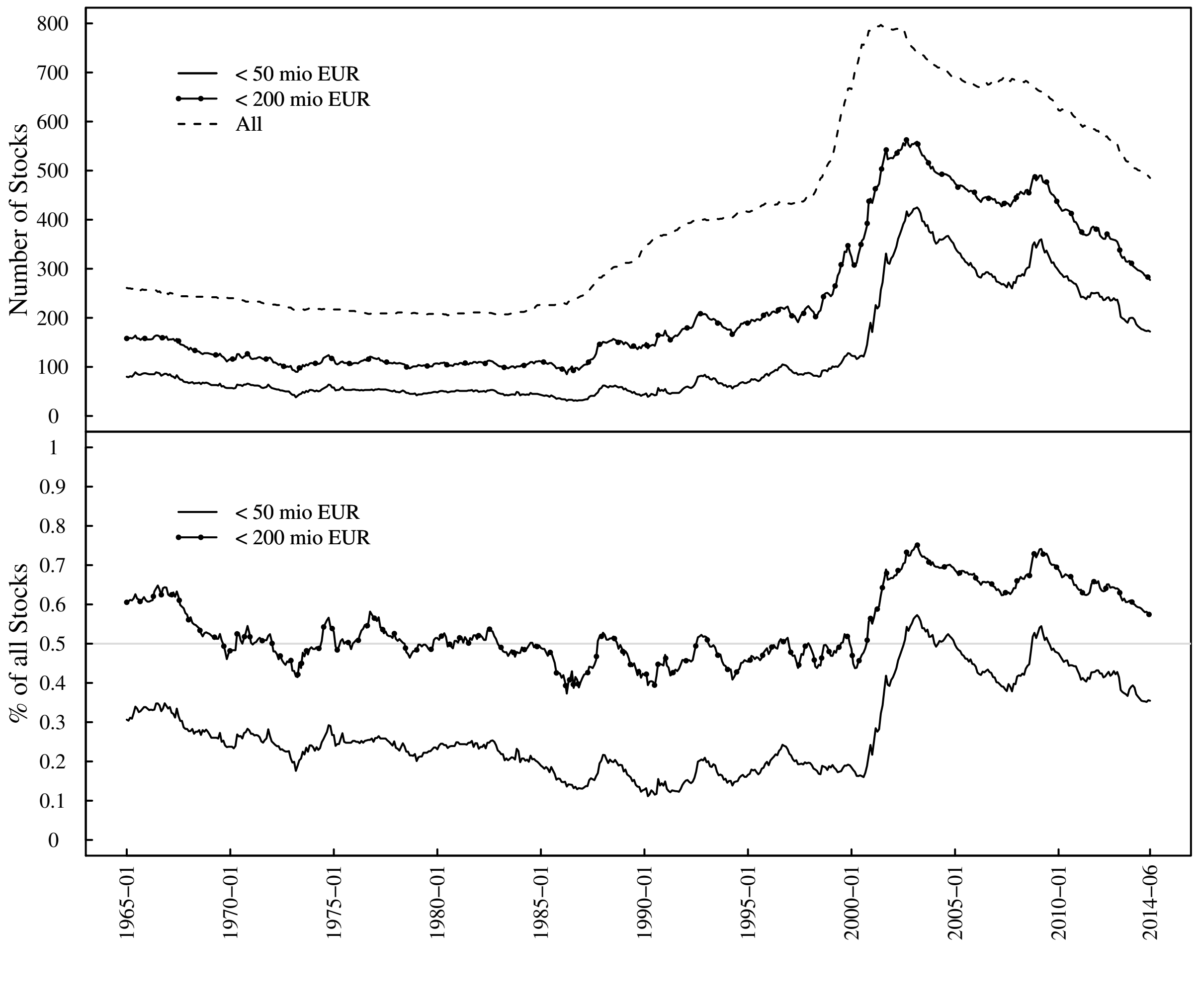
[16] The plot starts 1965 and not 1955 when the first data is available because portfolio formation begins in 1965.

[17] Limits in prices of December 2014 are recursively adjusted by inflation. Inflation rates are from the Federal Statistical Office as described in Stehle/Schmidt (2015). A €50 million stock in December 2014 is, e.g., equivalent to a €13.2 million stock as of January 1965 and €31.8 million as of January 1990.

€50 million increases dramatically. In 2002 and 2003, after the burst of the dotcom bubble, and again in 2008, when the financial crisis hit the market, more than 50% of the sample stocks are smaller than €50 million. The incredible increase in 2002 and 2003 is mainly related to the former Neuer Markt. Still today, about one third of all stocks available in the sample are smaller than €50 million.[18] The amount of stocks smaller than €200 million is considerably higher and make up about 60% in the sixties, around 50% afterwards, and more than two thirds after the turn of the millennium, peaking at around 75% in 2002 and 2003.

Figure 1: Number of Stocks Available in the Dataset

The dataset consists of all German common and preferred stocks with a listing in the top and middle segment, and stocks formally listed in the Neuer Markt of the Frankfurt Stock Exchange. The upper plot shows the total number of stocks (dotted line) available in the dataset between 1965 and 2014 along with the number of stocks with a market capitalization of less than €50 million (solid line) and less than €200 million (solid line with dots). The lower plot expresses the number of stocks in percentage of all stocks in the sample. The limits are in prices of December 2014, recursively adjusted by inflation, see Section 3 for details.



The exclusion of stocks smaller than €200 million would considerably reduce the sample and obviously not fulfill condition (1). Thus, the exclusion of stocks with a market capitalization of less than €50 million seems to be more appropriate. The limit of €50 million is, how-

[18] The issues discussed are not only relevant to this study. The large number of very small stocks has implications for numerous studies that deal with German stocks from 1997 onwards.

ever, still arbitrary and more closely aligned to the SEC's nanocap definition but appears to be reasonable in the German context.[19]

To investigate if microstructure effects solely drive profitable portfolio strategies, I consider two samples throughout this study. The first includes all German stocks listed in the top and middle segment, as well as the stocks from the former Neuer Markt of the Frankfurt Stock Exchange (no exclusions). The second sample is a sub-sample from the first, excluding stocks with a market capitalization of less than €50 million (in prices of December 2014, recursively adjusted by inflation). I refer to this sample as 'excluding microcap stocks'.

4. Patterns in German Stock Returns

This section studies the relationship between future and past stock returns for the German stock market. The purpose is to identify the historical (lagged) returns that seem to be best suited to specific momentum, contrarian, and seasonality strategies. In this context, the common procedure is to estimate Fama/MacBeth (1973) cross-sectional regressions (Jegadeesh (1990), Heston/Sadka (2008), Novy-Marx (2012), among others).

4.1 The Cross-Sectional Relationship between Future and Past Stock Returns

I first estimate univariate Fama/MacBeth (1973) cross-sectional regressions in each month t and lag k in the form of:

$$r_{i,t} = \alpha_{k,t} + \gamma_{k,t} r_{i,t-k} + e_{i,t}, \tag{1}$$

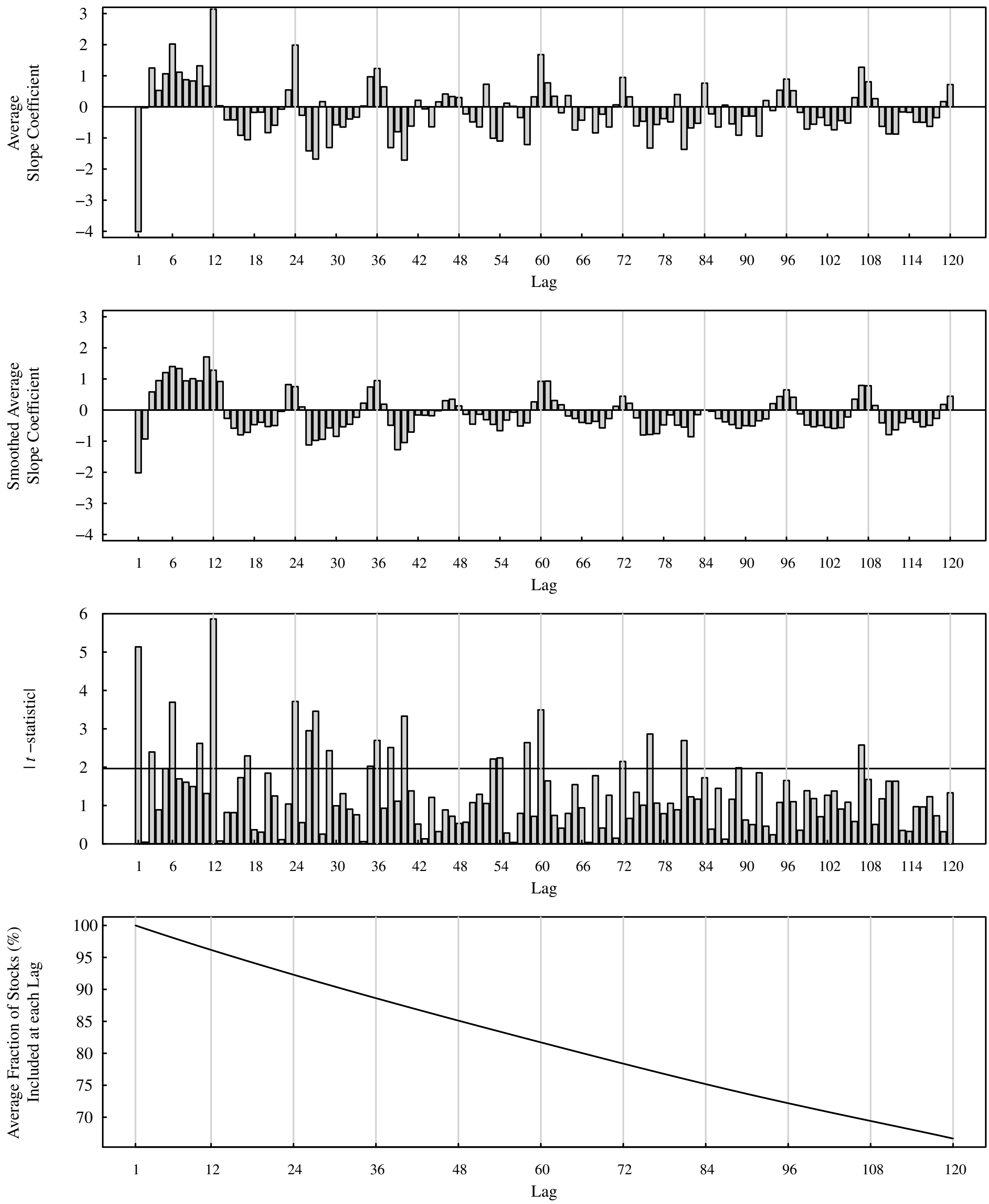
where $r_{i,t}$ is the stock return of stock i in month t, $r_{i,t-k}$ is the lagged stock return of stock i in month $t-k$, $\alpha_{k,t}$ the regression intercept and $\gamma_{k,t}$ the slope coefficient for the regression with lag k in month t. I estimate this regression in month $t = 1{:}\,01/1965$ to $t = 594 = T{:}\,06/2014$ for $k = 1,2 \dots,120$ lagged returns (altogether $594 * 120 = 71{,}280$ regressions). The regression at $t = 1$ with $k = 120$ requires data at 01/1965 and 01/1955, which is the beginning of the available return data. To be included in a regression in month t with lag k, a stock is required to have a valid return at month t and at month $t-k$. All German stocks listed in the top and middle segment, and the stocks from the former Neuer Markt of the Frankfurt Stock Exchange, are considered (no exclusions).

Figure 2 shows the results for the Fama/MacBeth regressions, with the top graph plotting a line through the 120 time series averages ($\times 10^2$) of the estimated slope coefficients $\hat{\gamma}_{k,t}$. (Table 2, column 'Univariate, A.I', reports the exact numbers up to lag 60.) The second graph plots a smoothed version of the time series averages (sum over the current, former, and next time series average divided by three). The third graph plots the |t-statistics| of the time series averages. The bottom graph plots the average percentage of stocks that have a valid return at

[19] As a robustness check I calculate all results in all cases also for a sample excluding stocks smaller than €200 million. The results are in all cases very similar to the results when excluding microcap stocks.

Figure 2: Fama-MacBeth Regression Results

This figure shows results from Fama-MacBeth regressions in the form of $r_{i,t} = \alpha_{k,t} + \gamma_{k,t} r_{i,t-k} + e_{i,t}$ where $r_{i,t}$ is the return of stock i in month t, $r_{i,t-k}$ is the lagged return of stock i in month $t-k$, $\alpha_{k,t}$ the regression intercept and $\gamma_{k,t}$ the slope coefficient for the regression with lag k in month t. The regression is estimated in month $t = 1{:}\,01/1965$ to $t = 594 = T{:}\,06/2014$ for $k = 1,2 \ldots 120$ lagged returns (altogether 71,280 regressions). The top graph plots a line through 120 time series averages ($\times\, 10^2$) of slope coefficients $\hat{\gamma}_{k,t}$. The second graph plots a smoothed version of the time series averages (sum over the current, former, and next time series average divided by three). The third graph plots the |t-statistics| for the time series averages. The bottom graph plots the average percentage of stocks out of all available stocks that have a valid return at month t and month $t-k$.



month t and month $t-k$, and thus are eligible to be included in a regression at month t with lag k.

The figure reveals a strong negative average coefficient for the first lag, representing the short-run stock reversal documented by Jegadeesh (1990). It is followed by positive, average coefficients up to lag twelve, which reflects momentum reported by Jegadeesh/Titman (1993). The plot also seems to reflect De Bondt/Thaler's (1985, 1987) long-term stock reversal, only interrupted by positive pulses at most of the multiple annual lags (12, 24, 36, 60, and 72). This result is equivalent to the pattern reported by Heston/Sadka (2008) for the U.S. stock market, although I find that the magnitude of the pulses at the annual lags seems to slightly decrease over time. This is in line with the result reported by Heston/Sadka (2010) in their cross-country study that includes Germany.

Second, I estimate multivariate Fama/MacBeth (1973) cross-sectional regressions similar to Jegadeesh (1990), to check the robustness of the results:[20]

$$r_{i,t} = \alpha_{j,t} + \sum_{k=1}^{j} \gamma_{k,t}\, r_{i,t-k} + e_{i,t}, \tag{2}$$

with $j \in \{12, 24, 36, 48, 60\}$. This specification is different from formula 1 as it includes all lags up to lag k in a regression at month t.

Table 2 reports the time series averages of estimated slope coefficients of the multivariate cross-sectional regressions in columns 4 to 13. The result for lag two of the univariate regressions (columns 2 and 3) is distinct from the result of the multivariate regressions (columns 4 to 13). The time series average in the univariate specification is -0.03 (t-statistic -0.04), and in the multivariate specification, all five time series averages are well under minus one and statistically significant (-1.15, -1.55, -1.81, -2.08, -1.90). This suggests that a contrarian strategy to exploit short-run stock reversals, originally reported by Jegadeesh (1990), may not only base the portfolio construction on the return from the previous month, but also on the return of two months ago.

The negative average coefficient at lag two in the multivariate regressions in addition questions the traditional momentum strategy that is based on the past returns over two to twelve months. This supports the argument of Gong et al. (2015), who assert that it is disadvantageous to include lag two. However, the average coefficients of lag three and four are, on average, statistically indistinguishable from zero. This suggests that, on average, the stock return over the past three and four months do not have predictive power and may also not be included when sorting portfolios for a momentum strategy. This seem to support the results reported by Novy-Marx (2012), who argues that a stock's performance over the past seven to twelve

[20] Appendix A in addition includes Fama-MacBeth regressions with single and/or compounded returns over certain contiguous and non-contiguous past horizons.

Table 2: Univariate and Multivariate Fama-MacBeth Regression Results

This table shows the results from univariate Fama-MacBeth regressions in the form of $r_{i,t} = \alpha_{k,t} + \gamma_{k,t} r_{i,t-k} + e_{i,t}$, where $r_{i,t}$ is the return of stock i in month t, $r_{i,t-k}$ is the lagged return of stock i in month $t-k$, $\alpha_{k,t}$ the regression intercept and $\gamma_{k,t}$ the slope coefficient for the regression with lag k in month t. The regression is estimated in month $t = 1{:}\,01/1965$ to $t = 594 = T{:}\,06/2014$ for $k = 1,2 \dots 60$ lagged returns (altogether 35,640 regressions). The estimated coefficients are multiplied by 10^2. Multivariate Fama-MacBeth regressions include all lagged returns up to lag j: $r_{i,t} = \alpha_{k,t} + \sum_{k=1}^{j} \gamma_{k,t} r_{i,t-k} + e_{i,t}$, with $j \in \{12, 24, 36, 48, 60\}$. Asterisks ***/**/* show significance at the 1/5/10% level.

	Univariate		Multivariate									
	A.I		B.I $j=12$		B.II $j=24$		B.III $j=36$		B.IV $j=48$		B.V $j=60$	
Lag	Average Coef.	t-stat.	Average Coef.	t-stat.	Average Coef.	t-stat.	Average Coef.	t-stat.	Average Coef.	t-stat.	Average Coef.	t-stat.
1	-4.01***	-5.14	-5.29***	-7.20	-6.00***	-8.50	-6.26***	-8.66	-6.56***	-9.09	-6.60***	-9.10
2	-0.03	-0.04	-1.15*	-1.93	-1.55***	-2.66	-1.81***	-3.07	-2.08***	-3.61	-1.90***	-3.14
3	1.25**	2.40	0.45	0.93	0.28	0.56	0.12	0.23	0.43	0.86	0.13	0.27
4	0.53	0.89	0.56	1.04	0.26	0.52	-0.01	-0.02	-0.08	-0.17	0.24	0.47
5	1.06*	1.96	1.05**	2.12	1.20**	2.39	1.05**	2.02	1.35***	2.72	1.37***	2.81
6	2.02***	3.69	1.74***	3.51	1.63***	3.30	1.32***	2.61	1.14**	2.27	1.15**	2.25
7	1.11*	1.69	1.26**	2.00	1.73***	2.79	1.73***	2.67	1.71**	2.42	1.54**	2.14
8	0.87	1.61	1.07**	2.20	1.14**	2.39	1.11**	2.29	1.00**	2.02	1.29**	2.46
9	0.83	1.49	1.08**	2.10	1.21**	2.40	1.40***	2.77	1.22**	2.52	1.06**	2.08
10	1.32***	2.62	1.54***	3.43	1.26***	2.99	1.14***	2.68	1.32***	3.08	1.02**	2.30
11	0.67	1.31	0.79*	1.65	0.97**	1.99	1.14**	2.36	1.34***	2.77	1.41***	2.88
12	3.14***	5.86	2.91***	6.10	3.49***	7.60	3.53***	7.68	3.37***	7.33	3.24***	7.03
13	0.03	0.07			0.52	1.20	0.50	1.16	0.24	0.56	0.05	0.11
14	-0.42	-0.82			-0.41	-0.93	-0.34	-0.73	-0.68	-1.46	-0.47	-0.96
15	-0.42	-0.81			-0.60	-1.28	-0.74	-1.54	-0.76	-1.57	-0.64	-1.21
16	-0.91*	-1.73			-0.83*	-1.73	-0.91*	-1.81	-0.84*	-1.69	-0.73	-1.45
17	-1.06**	-2.29			-0.76*	-1.79	-0.84*	-1.92	-0.76*	-1.73	-0.73	-1.56
18	-0.18	-0.37			-1.09**	-2.30	-1.19**	-2.46	-1.19**	-2.47	-1.05**	-2.06
19	-0.17	-0.31			-0.36	-0.69	-0.14	-0.26	-0.24	-0.45	-0.02	-0.04
20	-0.83*	-1.84			-0.62	-1.45	-0.63	-1.38	-0.71	-1.56	-1.02**	-2.11
21	-0.59	-1.25			-0.82**	-2.03	-0.70*	-1.65	-0.93**	-2.15	-0.62	-1.34
22	-0.07	-0.11			-0.23	-0.39	-0.20	-0.35	-0.17	-0.29	-0.06	-0.09
23	0.54	1.04			0.39	0.79	0.32	0.61	0.40	0.77	0.14	0.25
24	1.99***	3.71			1.55***	3.26	1.21**	2.45	1.19**	2.49	1.08**	2.20
25	-0.27	-0.55					-0.13	-0.29	0.01	0.01	0.00	0.00
26	-1.42***	-2.95					-0.94**	-2.10	-0.64	-1.39	-0.43	-0.94
27	-1.68***	-3.46					-1.01**	-2.29	-0.93**	-2.08	-1.07**	-2.44
28	0.17	0.26					0.03	0.05	0.07	0.14	0.01	0.03
29	-1.31**	-2.43					-1.02**	-2.17	-0.90*	-1.91	-0.64	-1.25
30	-0.58	-0.99					-0.57	-1.17	-0.41	-0.84	-0.77	-1.44
31	-0.65	-1.31					-0.18	-0.40	-0.34	-0.73	-0.32	-0.66
32	-0.39	-0.91					-0.05	-0.12	-0.16	-0.35	-0.46	-0.92
33	-0.33	-0.76					-0.70	-1.60	-0.53	-1.17	-0.65	-1.36
34	0.03	0.06					-0.45	-1.17	-0.41	-1.05	-0.31	-0.74
35	0.97**	2.02					0.60	1.39	0.59	1.35	0.39	0.87
36	1.23***	2.70					1.14***	2.77	1.33***	3.10	1.54***	3.55
37	0.64	0.93							1.00*	1.73	0.90	1.54
38	-1.31**	-2.51							-0.47	-0.94	-0.80	-1.60
39	-0.80	-1.11							-0.54	-0.93	-0.40	-0.65
40	-1.71***	-3.33							-1.30***	-2.70	-1.36***	-2.79
41	-0.62	-1.38							-0.61	-1.39	-0.50	-1.11

Table 2 continued.

	Univariate		Multivariate									
	A.I		B.I $j = 12$		B.II $j = 24$		B.III $j = 36$		B.IV $j = 48$		B.V $j = 60$	
Lag	Average Coef.	t-stat.	Average Coef.	t-stat.	Average Coef.	t-stat.	Average Coef.	t-stat.	Average Coef.	t-stat.	Average Coef.	t-stat.
42	0.21	0.52							-0.14	-0.35	-0.11	-0.28
43	-0.07	-0.13							0.06	0.14	-0.04	-0.09
44	-0.64	-1.21							-0.35	-0.63	-0.04	-0.07
45	0.16	0.32							0.11	0.26	0.52	1.20
46	0.41	0.89							0.49	1.10	1.00**	2.15
47	0.33	0.72							0.29	0.67	0.44	1.00
48	0.30	0.53							0.57	1.17	0.79	1.48
49	-0.23	-0.56									0.17	0.38
50	-0.48	-1.08									0.07	0.15
51	-0.65	-1.29									-0.77*	-1.82
52	0.73	1.05									0.06	0.13
53	-1.01**	-2.21									-0.39	-0.76
54	-1.10**	-2.24									-1.14**	-2.47
55	0.12	0.28									-0.15	-0.32
56	0.02	0.04									0.05	0.10
57	-0.34	-0.80									-0.51	-1.21
58	-1.21***	-2.64									-1.05**	-2.44
59	0.32	0.72									0.28	0.62
60	1.68***	3.49									1.13**	2.47

months in the U.S. better predict future returns than the traditional momentum sort based on two to twelve months.

Table 2 reveals positive pulses at multiple annual lags (12, 24, 36, 60, 72), but there is a distinct difference to the numbers reported by Heston/Sadka (2008) or Yao (2012): it appears that the average coefficients at the previous and next lag to the multiple annual lags (13, 23 and 25, 35 and 37, 59) follow their own pattern. The average coefficients for these lags are mostly positive, although close to zero (e.g., in specification B.V: $\overline{\hat{\gamma}_{13,t}} = 0.05$, $\overline{\hat{\gamma}_{23,t}} = 0.14$, $\overline{\hat{\gamma}_{25,t}} = 0.00$, $\overline{\hat{\gamma}_{35,t}} = 0.39$), but they are neither similar to the positive and significant multiple annual lags ($\overline{\hat{\gamma}_{12,t}} = 3.24$, $\overline{\hat{\gamma}_{24,t}} = 1.08$, $\overline{\hat{\gamma}_{36,t}} = 1.54$), nor to the usually negative and significant sub-annual lags ($\overline{\hat{\gamma}_{14,t}}, \dots, \overline{\hat{\gamma}_{22,t}} < 0$, $\overline{\hat{\gamma}_{26,t}}, \dots, \overline{\hat{\gamma}_{34,t}} < 0$ [except $\overline{\hat{\gamma}_{28,t}} = 0.01$], and $\overline{\hat{\gamma}_{38,t}}, \dots, \overline{\hat{\gamma}_{44,t}} < 0$). Consequently, the portfolio strategy proposed by Heston/Sadka (2008) may alternatively also include the previous and next lag to the multiple annual lags (13, 23 and 25, 35 and 37, 59). On the other hand, the long-term contrarian strategy that emerges from De Bondt/Thaler (1985, 1987) is obviously contaminated by the annual lags. This suggests excluding the multiple annual lags (and possibly also the previous and next lag to the multiple annual lags) from the past two to five years' performance.

4.2 Portfolio Formation and Strategies

In the formation of portfolios, I essentially follow Fama/French (1996). At the beginning of each month $t = 1{:}\,01/1965$ to $t = 594 = T{:}\,06/2014$, stocks are ranked according to the compounded total return over specific contiguous and non-contiguous lags.[21] Decile portfolios are formed based on this ranking and returns are either equal-weight or by the stock's market capitalization (value-weight) at the beginning of month t. To avoid unusual high weights when computing value-weight returns, the maximum weight per stock per portfolio is limited to 50%.[22] To be included in a sorting, each stock is required to be listed and to have a valid market capitalization available at the beginning of month t, as well as to have valid return data available at the specific lags considered for a given strategy. Stocks with unavailable return data in the time period after formation (i.e., during the holding period) due to a delisting, etc., are kept with a zero return until the next rebalancing.[23] The sorting procedure is repeated at the beginning of every month (=monthly rebalanced).[24]

Table 3: Portfolio Formation

This table shows the lags included in portfolio formations of various momentum, contrarian, and seasonality strategies. A strategy and time series of monthly returns is denoted as $r_{n,m}$, with n, m referring to the (contiguous or non-contiguous) performance over past month m to past month n considered when sorting stocks to portfolios ($n \leq m$). For example, $r_{2,12}$ refers to the 2-12 momentum strategy and its time series of monthly returns that is based on the performance of individual stocks over the past two to twelve months prior to portfolio formation.

Strategy\Lag		1	2	3	4	5	6	7	…	11	12	13	14	…	22	23	24	25	26	…	34	35	36	37	38	…	46	47	48	49	50	…	58	59	60
Short-Term Contrarian	$r_{1,1}$	•																																	
	$r_{1,2}$	•	•																																
Momentum	$r_{2,12}$		•	•	•	•	•	•	•	•	•																								
	$r_{3,12}$			•	•	•	•	•	•	•	•																								
	$r_{7,12}$							•	•	•	•																								
Long-Term Contrarian	$r_{25,60}$																	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
	$r_{13,60}$											•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
	$r_{13,60}^{ex\ annual}$											•	•	•	•	•		•	•	•	•	•		•	•	•	•	•		•	•	•	•	•	
	$r_{13,60}^{ex\ annual+}$												•	•	•				•	•	•				•	•	•				•	•	•		
Seasonality	r^{annual}										•						•						•						•						•
	$r^{annual+}$									•	•	•				•	•	•				•	•	•				•	•	•				•	•

[21] Alternatively, portfolio formation could be based on cumulative returns, see e.g. Grundy/Martin (2001) for the motivation.

[22] This limit is exceeded in about 12% of all decile portfolios of all strategies of Table 3.

[23] Alternatively, the amount invested in the delisted stock could be allocated to the remaining stocks. However, since all conclusions are based on strategies with monthly rebalancing the two approaches should have similar results.

[24] Holding periods of longer than one month, this is rebalancing after e.g. three, six, or twelve months are also considered but not discussed in this paper. The results can be found in the Appendix D. Monthly rebalancing dominates in most of the cases the longer rebalancing intervals.

The return of a given momentum or seasonality (contrarian) strategy is the return of decile portfolio ten (one) minus the return of decile portfolio one (ten). A strategy and time series of monthly returns is denoted as $r_{n,m}$, with n, m referring to the (contiguous or non-contiguous) performance over past month m to past month n considered when sorting stocks to portfolios ($n \leq m$). For example, $r_{2,12}$ refers to the 2-12 momentum strategy and its time series of monthly returns that is based on the performance of individual stocks over the past two to twelve months prior to portfolio formation. The strategies included are the (traditional) contrarian, momentum, and seasonality strategies, and in addition the alternative version suggested by the Fama/MacBeth regressions results obtained in Section 4.1. Table 3 shows all strategies considered and the corresponding lags included.

5. Returns of Momentum, Contrarian, and Seasonality Strategies

This section reports the returns of selected contrarian, momentum, and seasonality strategies. Included are traditional strategies and their modified versions. The results are shown in Table 4 and are discussed, panel-by-panel, in the next sections. The table shows averages of monthly raw returns and alphas obtained from one factor (Jensen (1968)), three factor (Fama/French (1993)) and four factor (Carhart (1997)) regressions for the full time period of fifty years and five 10-year sub-periods.[25] Table 5, in addition, shows the differences between the strategies' average monthly raw returns. Reported are results for a sample of all stocks of all sizes and, in addition, for a sub-sample that excludes microcap stocks (stocks with a market capitalization of less than €50 million in prices of December 2014 are recursively adjusted by inflation, see Section 3 for details).[26]

5.1 Momentum Strategies

Panel A of Table 4 shows the results for momentum strategies. All three strategies earn significant average raw returns over the full 50-year time period. The standard 2-12 strategy, $r_{2,12}$, earns 0.77% per month when equal-weighting and all stocks are considered; when value-weighting, the average monthly raw return is 1.76%. For the same time period, the average return for this strategy in the U.S. is 0.95% (equal-weight) and 1.31% (value-weight), which are quite similar.[27] After excluding microcap stocks, momentum strategies still seem to provide large average returns. This suggests that momentum does not only rely on small stocks and appears to be significant in German stock returns, which is in line with prior research (see Section 2.3, literature review).

[25] All benchmark data and factor time series are taken from Richard Stehle's data library available at http://www.wiwi.hu-berlin.de/professuren/bwl/bb/data and described in Brückner/Lehmann/Schmidt/Stehle (2015a). I use the data set 'ALL' with breakpoints from the top segment.

[26] Table A. 2 in Appendix B contains some descriptive statistics for all strategies.

[27] The numbers are based on Kenneth French's data library, "10 Portfolios Formed on Momentum", available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html (June 24, 2015).

Table 4: Returns on Various Momentum, Contrarian, and Seasonality Strategies

At the beginning of each month $t = 1{:}01/1965$ to $t = 594 = T{:}06/2014$ stocks are ranked according to the compounded total return over specific contiguous and non-contiguous lags (see Table 3 for details). Decile portfolios are formed based on this ranking and returns are equal-weight or by the stock's market capitalization (value-weight) at the beginning of month t. In value-weight portfolios the maximum weight is limited to 50%. Decile portfolios are rebalanced monthly. A given momentum or seasonality (contrarian) strategy is short (long) in decile one and long (short) in decile ten.

Presented are average monthly raw returns and alphas obtained from one factor (Jensen (1968)), three factor (Fama/French (1993)) and four factor (Carhart (1997)) regressions. Shown are results for a sample of all stocks of all sizes and in addition for a sub-sample that excludes microcap stocks (<€50 mio, recursively adjusted by inflation, see Section 3 for details). Test statistics for alphas are based on Newey-West standard errors. Asterisks ***/**/* show significance at the 1/5/10% level.

	Value-Weight Returns						Equal-Weight Returns					
	Full Period	10 year Sub-Periods					Full Period	10 year Sub-Periods				
	1965 - 2014	1965 - 1974	1975 - 1984	1985 - 1994	1995 - 2004	2005 - 2014	1965 - 2014	1965 - 1974	1975 - 1984	1985 - 1994	1995 - 2004	2005 - 2014
Panel A: Momentum												
$r_{2,12}$												
Sample: All												
Raw	1.76***	0.47	1.18**	1.05**	2.95***	3.22**	0.77**	0.70*	1.08***	1.24***	2.38**	-1.68
1F-alpha	1.92***	0.39	1.17***	1.12**	3.18***	3.95***	0.92***	0.62	1.10***	1.34***	2.61***	-1.16
3F-alpha	1.92***	0.27	1.18***	0.86*	2.19**	4.67***	0.81***	0.61	1.10***	1.18***	1.55**	-1.11
4F-alpha	0.54**	0.10	0.18	0.37	0.28	1.90**	0.04	0.46	0.35	0.73**	0.28	-1.68
Sample: Excluding Microcap Stocks												
Raw	1.57***	0.46	1.36***	1.09**	2.70**	2.27*	1.70***	0.46	1.05***	1.36***	3.61***	2.02***
1F-alpha	1.72***	0.38	1.33***	1.14***	2.94***	2.94**	1.85***	0.38	1.05***	1.45***	3.90***	2.45***
3F-alpha	1.75***	0.29	1.33***	0.89**	2.17**	3.55***	1.70***	0.23	1.05***	1.26***	3.05***	2.52***
4F-alpha	0.33	0.11	0.31	0.43	0.17	0.59	0.72***	0.07	0.19	0.81***	1.56***	1.09**
$r_{3,12}$												
Sample: All												
Raw	2.00***	0.70*	1.61***	0.84*	2.54**	4.42***	0.85***	0.65	1.40***	1.09**	2.39***	-1.39
1F-alpha	2.16***	0.63*	1.61***	0.90**	2.77**	5.19***	0.99***	0.58	1.42***	1.16***	2.61***	-0.94
3F-alpha	2.15***	0.52	1.61***	0.65	1.60	5.71***	0.87***	0.64*	1.42***	1.03***	1.57**	-0.88
4F-alpha	0.89***	0.36	0.78**	0.21	-0.14	3.27***	0.16	0.48	0.84**	0.60**	0.42	-1.50
Sample: Excluding Microcap Stocks												
Raw	1.48***	0.45	1.39***	0.72	1.92*	2.97***	1.62***	0.54	1.06***	1.11***	3.18***	2.26***
1F-alpha	1.62***	0.36	1.41***	0.77*	2.09**	3.67***	1.76***	0.47	1.08***	1.19***	3.44***	2.64***
3F-alpha	1.69***	0.30	1.41***	0.53	1.39	4.39***	1.62***	0.41	1.08***	1.04**	2.59***	2.74***
4F-alpha	0.47**	0.13	0.53	0.09	-0.41	2.17**	0.71***	0.26	0.34	0.62**	1.24**	1.34***
$r_{7,12}$												
Sample: All												
Raw	1.22***	0.64**	1.34***	1.53***	1.10	1.50	0.63*	0.36	1.07***	1.28***	1.51*	-1.17
1F-alpha	1.27***	0.60*	1.25***	1.54***	1.13	1.89*	0.74**	0.30	1.08***	1.34***	1.64*	-0.67
3F-alpha	1.34***	0.56	1.25***	1.41***	0.58	2.78***	0.73**	0.47	1.08***	1.21***	0.92	-0.40
4F-alpha	0.39	0.43	0.50	1.04**	-0.75	0.94	0.24	0.36	0.50	0.88***	0.02	-0.40
Sample: Excluding Microcap Stocks												
Raw	1.35***	0.43	1.12***	1.38***	1.44	2.40**	1.43***	0.51*	1.10***	1.14***	2.60***	1.82***
1F-alpha	1.42***	0.39	1.03***	1.40***	1.55*	2.87**	1.51***	0.46*	1.04***	1.20**	2.74***	2.07***
3F-alpha	1.50***	0.33	1.03***	1.28***	1.17	3.62***	1.48***	0.48	1.04***	1.09**	2.28***	2.25***
4F-alpha	0.56**	0.23	0.44	0.91**	-0.15	1.72**	0.83***	0.38	0.50*	0.77**	1.33*	1.27***

Table 4 continued.

	Value-Weight Returns						Equal-Weight Returns					
	Full Period	10 year Sub-Periods					Full Period	10 year Sub-Periods				
	1965 - 2014	1965 - 1974	1975 - 1984	1985 - 1994	1995 - 2004	2005 - 2014	1965 - 2014	1965 - 1974	1975 - 1984	1985 - 1994	1995 - 2004	2005 - 2014
Panel B: Short-Term Contrarian												
$r_{1,1}$												
Sample: All												
Raw	0.02	0.45	0.53	0.19	-0.68	-0.42	1.93***	1.02***	0.72**	1.05***	1.49	5.56***
1F-alpha	-0.09	0.49	0.50	0.09	-0.88	-0.76	1.83***	1.08***	0.71**	0.92***	1.36	5.32***
3F-alpha	-0.06	0.59	0.49	0.25	-0.25	-0.72	1.89***	1.22***	0.71**	1.11***	1.98*	5.73***
4F-alpha	0.57*	0.67	1.14***	0.26	0.95	0.39	2.22***	1.27***	0.93***	1.16***	2.82**	6.09***
Sample: Excluding Microcap Stocks												
Raw	0.01	0.43	0.59	0.39	-0.77	-0.61	0.51**	0.92***	0.90***	0.82**	-0.25	0.13
1F-alpha	-0.09	0.47	0.58*	0.30	-1.01	-0.84	0.41**	0.97***	0.92***	0.70**	-0.46	-0.02
3F-alpha	-0.09	0.53	0.57*	0.43	-0.59	-0.57	0.48*	1.16***	0.92***	0.88**	0.06	0.19
4F-alpha	0.40	0.60	1.20***	0.44	0.46	0.00	0.96***	1.22***	1.30***	0.94***	1.27	0.53
$r_{1,2}$												
Sample: All												
Raw	-0.16	0.40	0.11	0.18	-0.21	-1.33	1.61***	0.84**	0.59*	0.78*	1.02	5.00***
1F-alpha	-0.31	0.48	0.15	0.11	-0.53	-1.74*	1.46***	0.92***	0.57*	0.64*	0.83	4.48***
3F-alpha	-0.07	0.70*	0.15	0.32	0.35	-0.91	1.54***	1.11***	0.57*	0.78**	1.79	4.59***
4F-alpha	0.54*	0.79**	0.88**	0.47	1.36	0.06	2.07***	1.17***	1.09***	0.94***	3.08***	4.78***
Sample: Excluding Microcap Stocks												
Raw	-0.13	0.43	0.01	0.33	-0.51	-0.96	0.01	0.67**	0.54	0.46	-1.34	-0.30
1F-alpha	-0.26	0.50	0.00	0.25	-0.74	-1.31	-0.11	0.74**	0.53	0.33	-1.58*	-0.53
3F-alpha	-0.07	0.71**	0.00	0.44	-0.09	-0.74	0.00	0.96***	0.53	0.40	-0.85	-0.36
4F-alpha	0.53**	0.79**	0.77**	0.59	1.08	0.06	0.65***	1.03***	1.21***	0.56	0.68	0.12
Panel C: Seasonality												
r^{annual}												
Sample: All												
Raw	1.22***	0.87***	1.35***	1.14***	1.76***	0.95	0.85***	0.96***	0.80***	1.27***	1.64***	-0.48
1F-alpha	1.19***	0.85***	1.34***	1.06***	1.62**	1.08	0.85***	0.95***	0.84***	1.17***	1.67***	-0.45
3F-alpha	1.31***	0.88***	1.34***	1.18***	1.61**	1.02	0.90***	1.00***	0.84***	1.29***	1.55***	-0.49
4F-alpha	1.07***	0.84***	1.21***	1.14***	1.28*	0.35	0.81***	0.99***	0.65***	1.28***	1.50***	-0.71
Sample: Excluding Microcap Stocks												
Raw	1.04***	0.48*	1.47***	1.12***	1.33**	0.79	1.02***	0.50**	1.08***	1.16***	1.82***	0.50
1F-alpha	1.02***	0.47*	1.45***	1.05**	1.20*	1.00	1.01***	0.50**	1.14***	1.08***	1.81***	0.57
3F-alpha	1.14***	0.51*	1.45***	1.11***	1.15	1.18	1.09***	0.56**	1.14***	1.22***	1.84***	0.50
4F-alpha	0.88***	0.48*	1.38***	1.09**	0.70	0.53	1.00***	0.56**	1.08***	1.22***	1.57***	0.41
$r^{annual+}$												
Sample: All												
Raw	1.07***	1.01***	1.76***	0.84*	1.64**	0.05	0.68***	0.73***	1.04***	0.77**	1.30***	-0.49
1F-alpha	1.01***	0.99***	1.76***	0.79*	1.40**	0.00	0.69**	0.72***	1.06***	0.74**	1.32***	-0.47
3F-alpha	1.24***	1.00***	1.77***	1.12**	1.05	0.64	0.77***	0.92***	1.07***	1.08***	1.01**	-0.70
4F-alpha	1.08***	1.03***	1.52***	1.08**	1.19*	-0.23	0.77***	0.95***	1.02***	1.09***	1.02**	-0.76
Sample: Excluding Microcap Stocks												
Raw	0.84***	0.79***	1.84***	0.45	0.95	0.12	0.98***	0.71***	1.21***	0.47	1.68***	0.84**
1F-alpha	0.82***	0.76***	1.86***	0.43	0.84	0.21	1.00***	0.69***	1.26***	0.45	1.68***	0.94**
3F-alpha	1.04***	0.77***	1.87***	0.77*	0.70	0.75	1.16***	0.77***	1.26***	0.79***	1.57***	1.10***
4F-alpha	0.77***	0.80***	1.56***	0.75*	0.22	0.01	1.05***	0.80***	1.08***	0.80***	1.36***	0.93**

Table 4 continued.

	Value-Weight Returns						Equal-Weight Returns					
	Full Period	10 year Sub-Periods					Full Period	10 year Sub-Periods				
	1965 - 2014	1965 - 1974	1975 - 1984	1985 - 1994	1995 - 2004	2005 - 2014	1965 - 2014	1965 - 1974	1975 - 1984	1985 - 1994	1995 - 2004	2005 - 2014
Panel D: Long-Term Contrarian												
$r_{25,60}$												
Sample: All												
Raw	-0.15	-0.45	0.07	0.36	-1.36**	0.70	0.58*	0.03	0.39	0.50	-0.35	2.43
1F-alpha	-0.10	-0.46	-0.16	0.44	-1.20**	0.81	0.58*	0.03	0.21	0.54	-0.29	2.40
3F-alpha	-0.46*	-0.38	-0.17	-0.05	-1.06**	0.06	0.44	0.04	0.20	0.17	-0.02	2.54
4F-alpha	-0.52**	-0.32	-0.01	-0.16	-1.40**	0.01	0.30	0.04	0.26	0.06	-0.31	2.29
Sample: Excluding Microcap Stocks												
Raw	-0.25	-0.38	0.43	0.37	-1.70***	0.04	-0.01	-0.07	0.31	0.57	-0.71*	-0.17
1F-alpha	-0.21	-0.38	0.19	0.44	-1.51***	0.00	-0.02	-0.07	0.07	0.60	-0.64	-0.27
3F-alpha	-0.53**	-0.31	0.18	-0.02	-1.47***	-0.09	-0.23	0.02	0.06	0.20	-0.68*	-0.35
4F-alpha	-0.58***	-0.27	0.35	-0.11	-1.67***	-0.21	-0.30*	0.02	0.17	0.06	-0.84**	-0.39
$r_{13,60}$												
Sample: All												
Raw	-0.09	-0.13	-0.06	0.57	-1.11	0.27	0.49	0.23	0.20	0.45	-0.50	2.15
1F-alpha	-0.08	-0.09	-0.33	0.67	-1.05	0.42	0.48	0.26	-0.02	0.50	-0.49	2.17
3F-alpha	-0.49*	-0.01	-0.34	0.24	-0.55	-0.90	0.33	0.30	-0.02	0.17	-0.06	2.14
4F-alpha	-0.20	0.00	-0.16	0.23	-0.25	-0.16	0.32	0.31	0.05	0.15	-0.12	1.99
Sample: Excluding Microcap Stocks												
Raw	0.09	0.03	-0.17	0.66	-0.92	0.87	-0.13	0.11	0.00	0.55	-1.02**	-0.29
1F-alpha	0.09	0.08	-0.42	0.73	-0.81	0.79	-0.16	0.15	-0.24	0.58	-0.96*	-0.48
3F-alpha	-0.28	0.15	-0.44	0.28	-0.63	0.26	-0.38**	0.16	-0.25	0.21	-0.88**	-0.76*
4F-alpha	-0.08	0.17	-0.24	0.28	-0.43	0.87	-0.31*	0.18	-0.16	0.18	-0.76*	-0.61
$r_{13,60}^{ex\ annual}$												
Sample: All												
Raw	0.08	0.41	0.21	1.17**	-1.15*	-0.27	0.81**	0.76***	0.37	0.91**	-0.34	2.46*
1F-alpha	0.10	0.45	0.02	1.27**	-1.02	-0.22	0.80**	0.80***	0.18	0.93**	-0.33	2.48*
3F-alpha	-0.32	0.45*	0.01	0.80	-0.65	-1.61	0.64**	0.78***	0.17	0.56	0.00	2.47*
4F-alpha	-0.05	0.48*	0.26	0.76	-0.48	-0.85	0.60**	0.79***	0.22	0.57	-0.12	2.24*
Sample: Excluding Microcap Stocks												
Raw	0.41*	0.27	0.55	1.07**	-0.64	0.79	0.19	0.44*	0.39	1.06***	-0.54	-0.45
1F-alpha	0.40	0.31	0.34	1.17**	-0.55	0.61	0.16	0.48**	0.18	1.09**	-0.49	-0.64
3F-alpha	0.06	0.35	0.33	0.68	-0.28	0.20	-0.06	0.46**	0.17	0.71*	-0.40	-0.91**
4F-alpha	0.26	0.37	0.65*	0.65	-0.22	0.83	0.01	0.48**	0.26	0.68	-0.38	-0.67
$r_{13,60}^{ex\ annual+}$												
Sample: All												
Raw	0.25	0.62*	0.83**	0.87**	-1.00	-0.08	0.93***	0.76***	0.71**	0.81**	-0.02	2.50*
1F-alpha	0.31	0.65*	0.66*	0.96**	-0.78	-0.03	0.92***	0.77***	0.49**	0.86**	-0.01	2.49
3F-alpha	-0.19	0.55*	0.65*	0.77*	-0.63	-1.74*	0.78**	0.76***	0.49**	0.62	0.26	2.48
4F-alpha	0.08	0.59*	0.88**	0.76*	-0.49	-1.10	0.74**	0.79***	0.58*	0.66	0.12	2.15
Sample: Excluding Microcap Stocks												
Raw	0.35	0.40	0.80**	0.74*	-0.50	0.31	0.28*	0.51**	0.80**	0.69*	-0.30	-0.32
1F-alpha	0.38	0.43	0.65*	0.83*	-0.32	0.23	0.27	0.54**	0.59**	0.75*	-0.24	-0.48
3F-alpha	0.02	0.42	0.64*	0.56	-0.45	-0.06	0.04	0.48**	0.58**	0.43	-0.26	-0.77**
4F-alpha	0.12	0.44	0.86**	0.55	-0.33	0.07	0.10	0.49**	0.62**	0.45	-0.25	-0.65*

Table 5: Differences between Average Monthly Raw Returns

At the beginning of each month $t = 1{:}\,01/1965$ to $t = 594 = T{:}\,06/2014$ stocks are ranked according to the compounded total return over specific contiguous and non-contiguous lags (see Table 3 for details). Decile portfolios are formed based on this ranking and returns are equal-weight or by the stock's market capitalization (value-weight) at the beginning of month t. In value-weight portfolios the maximum weight is limited to 50%. Decile portfolios are rebalanced monthly. A given momentum or seasonality (contrarian) strategy is short (long) in decile one and long (short) in decile ten.

Presented are the differences between average monthly raw returns. Shown are results for a sample of all stocks (Panel A) of all sizes and in addition for a sub-sample (Panel B) that excludes microcap stocks (<€50 mio, recursively adjusted by inflation, see Section 3 for details). Asterisks ***/**/* show significance at the 1/5/10% level

	Value-Weight Returns						Equal-Weight Returns					
	Full Period	10 year Sub-Periods					Full Period	10 year Sub-Periods				
	1965 - 2014	1965 - 1974	1975 - 1984	1985 - 1994	1995 - 2004	2005 - 2014	1965 - 2014	1965 - 1974	1975 - 1984	1985 - 1994	1995 - 2004	2005 - 2014
Panel A: All Stocks												
Short-Term Contrarian Strategies												
$r_{1,1} - r_{1,2}$	0.18	0.05	0.42	0.01	-0.47	0.91	0.32	0.18	0.14	0.26	0.47	0.55
Momentum Strategies												
$r_{2,12} - r_{3,12}$	-0.24	-0.24	-0.43**	0.21	0.40	-1.20*	-0.08	0.05	-0.32**	0.15	-0.01	-0.30
$r_{2,12} - r_{7,12}$	0.54*	-0.18	-0.16	-0.48	1.85	1.72*	0.14	0.33	0.01	-0.04	0.87	-0.51
$r_{3,12} - r_{7,12}$	0.78**	0.06	0.27	-0.69*	1.45	2.92***	0.22	0.29	0.33	-0.19	0.88	-0.22
Long-Term Contrarian Strategies												
$r_{25,60} - r_{13,60}$	-0.05	-0.32	0.13	-0.22	-0.25	0.42	0.09	-0.21	0.18	0.05	0.15	0.28
$r_{25,60} - r_{13,60}^{ex\,annual}$	-0.22	-0.86***	-0.15	-0.81**	-0.21	0.97	-0.23*	-0.74***	0.01	-0.40	-0.01	-0.02
$r_{25,60} - r_{13,60}^{ex\,annual+}$	-0.40	-1.08***	-0.76**	-0.52	-0.36	0.78	-0.35**	-0.73***	-0.32	-0.31	-0.33	-0.06
$r_{13,60} - r_{13,60}^{ex\,annual}$	-0.17	-0.53***	-0.27	-0.60**	0.04	0.55	-0.32***	-0.53***	-0.17	-0.45**	-0.16	-0.30
$r_{13,60} - r_{13,60}^{ex\,annual+}$	-0.35	-0.75**	-0.88***	-0.30	-0.11	0.36	-0.44***	-0.52***	-0.50**	-0.36	-0.48*	-0.34
$r_{13,60}^{ex\,ann.} - r_{13,60}^{ex\,ann.+}$	-0.17	-0.22	-0.61***	0.30	-0.15	-0.19	-0.12	0.01	-0.33*	0.09	-0.32	-0.04
Seasonality Strategies												
$r^{annual} - r^{annual+}$	0.15	-0.15	-0.41	0.29	0.12	0.90	0.17	0.23	-0.24	0.50*	0.34	0.00
Panel B: Excluding Microcap Stocks												
Short-Term Contrarian Strategies												
$r_{1,1} - r_{1,2}$	0.14	0.00	0.58	0.06	-0.26	0.35	0.50***	0.25	0.36	0.36	1.09**	0.42
Momentum Strategies												
$r_{2,12} - r_{3,12}$	0.09	0.01	-0.03	0.37	0.78	-0.70	0.08	-0.08	0.00	0.25*	0.43*	-0.23
$r_{2,12} - r_{7,12}$	0.23	0.03	0.24	-0.29	1.26	-0.13	0.27*	-0.05	-0.05	0.22	1.01**	0.20
$r_{3,12} - r_{7,12}$	0.13	0.02	0.27	-0.67*	0.48	0.57	0.19	0.03	-0.04	-0.03	0.58	0.44
Long-Term Contrarian Strategies												
$r_{25,60} - r_{13,60}$	-0.34*	-0.41	0.60**	-0.29	-0.78	-0.83	0.12	-0.17	0.30*	0.03	0.30	0.12
$r_{25,60} - r_{13,60}^{ex\,annual}$	-0.66***	-0.65**	-0.12	-0.70*	-1.06**	-0.76	-0.20*	-0.51**	-0.09	-0.48*	-0.17	0.28
$r_{25,60} - r_{13,60}^{ex\,annual+}$	-0.60***	-0.78**	-0.37	-0.37	-1.20**	-0.27	-0.29**	-0.58**	-0.49**	-0.12	-0.42	0.16
$r_{13,60} - r_{13,60}^{ex\,annual}$	-0.32**	-0.24	-0.72***	-0.41	-0.28	0.07	-0.31***	-0.33**	-0.39***	-0.51**	-0.48***	0.16
$r_{13,60} - r_{13,60}^{ex\,annual+}$	-0.26	-0.37	-0.97***	-0.08	-0.42	0.56	-0.41***	-0.40**	-0.79***	-0.14	-0.72**	0.04
$r_{13,60}^{ex\,ann.} - r_{13,60}^{ex\,ann.+}$	0.06	-0.13	-0.24	0.33	-0.14	0.49	-0.09	-0.07	-0.40**	0.37	-0.25	-0.12
Seasonality Strategies												
$r^{annual} - r^{annual+}$	0.21	-0.30	-0.37	0.67	0.38	0.67	0.04	-0.21	-0.14	0.69**	0.14	-0.33

When all stocks are considered, the strategy's raw returns with value-weight returns are typically more than twice as when equal-weighting is applied (e.g. $r_{2,12}$: 1.76% vs. 0.77%). When microcap stocks are excluded, on the other hand, the strategy's raw returns are similar (e.g., $r_{2,12}$: 1.57% vs. 1.70%). The increase from 0.77% to 1.70% in equal-weight returns when switching the samples suggests that momentum is less profitable in microcap stocks than it is in midcap and largecap stocks. Hong et al. (2000) have also found the same result for the U.S., reporting that momentum for the smallest stocks (in their sample, they have a mean market capitalization of $7 million) is negative. Similar, Glaser/Weber (2003) argue for Germany that momentum is mainly driven by the stocks of medium-sized firms.

The momentum strategy that is based on the performance over the past three to twelve months produces the largest returns (2.00% value-weight, all stocks), slightly larger than momentum strategy based on two to twelve months (1.76%). The opposite can be found when microcap stocks are excluded (1.48% vs. 1.57%). However, in last 10-year sub-period, the $r_{3,12}$ strategy dominates the $r_{2,12}$ strategy in both samples. When all stocks are considered, the difference of -1.20%-points between the two strategies is statistically significant, but not when microcap stocks are excluded (-0.70%-points, see Table 5). The evidence reported by Gong/Liu/Liu (2015) who argue that momentum strategies in the U.S. can be improved by excluding lag two thus seems to hold true for the German stock market as well.

The $r_{7,12}$ strategy suggested by Novy-Marx (2012) appears to be less profitable than the other two in nearly all setups and sub-periods. When all stocks are considered, the difference between the $r_{7,12}$ strategy (1.22%) and the $r_{3,12}$ strategy (2.00%) is 0.78%-points and is statistically significant on the 5% level. However, the same cannot be found when microcap stocks are excluded; the difference is only 0.13%-points and statistically insignificant. Nevertheless, in summary the results for Germany are less in favor of Novy-Marx (2012) and seem to support Yao (2012) and Gong et al. (2015).

The first 10-year sub-period from 1965 to 1974 reveals a distinct pattern. The raw returns earned from the three strategies are well below 1% and are mostly statistically insignificant. The alphas obtained from Fama/French's (1993) three-factor model are all statistically insignificant. Based on risk-adjusted returns, momentum strategies thus did not earn abnormal returns between 1965 and 1974. On the other hand, momentum strategies appear to be very profitable in more recent years, from 2005 to 2014. The $r_{3,12}$ strategy earned, on average, a monthly return of 2.97% with value-weight returns and excluding microcap stocks. Slightly smaller but nevertheless still very high is the average return when equal-weighting is applied (2.26%). The two other strategies also show large raw returns in the last 10 years, which are all above the 50-year averages for both value- and equal-weight returns. This result is very different from the U.S., where the returns of momentum strategies have decreased rather than increased (Hwang/Rubesam (2015)). Based on Kenneth French's data library (see Footnote 27), the average monthly return for the 2-12 strategy in the U.S. over the exact same period from 01/2005 to 06/2014 is 0.28% (value-weight) and 0.04% (equal-weight). Hence, momentum appears to be strong and persistent in German stock returns, even today – more than twenty years after its discovery by Jegadeesh/Titman in 1993.

The large raw returns cannot be explained by the four-factor model, which includes a momentum factor added to the Fama/French three-factor model. For the $r_{3,12}$ strategy in the time period from 2005 to 2014, and excluding microcap stocks, the alpha is 2.17% and highly statistically significant (1.34% when equal-weighting).[28] Similar are the results for the $r_{7,12}$ strategy. The essence of these results is to possibly revise the calculation procedure of the momentum factor for Germany.[29] As Brückner/Lehmann/Schmidt/Stehle (2015b) point out, exporting a factor (model) to a non-U.S. stock market should be handled with care.

5.2 Short-Term Contrarian Strategies

Panel B of Table 4 shows returns for two short-term contrarian strategies in which stocks that have performed badly are purchased and stocks that have performed well are sold. The first strategy $r_{1,1}$ takes only the return of the previous month into account to judge whether a performance was bad or good (relatively, to the rest of the stock universe). The second strategy $r_{1,2}$ in addition takes the penultimate month into account. It is motivated by the results obtained from the Fama-MacBeth regressions in Section 4.1.

Over the full period of fifty years, both strategies have high and statistically significant average monthly raw returns (1.93% and 1.61%) when equal-weighting is applied and all stocks are considered. Also based on equal-weight returns, Bromann et al. (1997) report for the $r_{1,1}$ strategy 1.19% per month, but conjecture that the returns might disappear when transaction costs are considered. On the other hand, when value-weighting is applied, neither strategies seem to have earned significant positive returns. The raw returns in the full-period and most sub-periods are close to zero and never statistically significant. This result points to an important pattern: both strategies seem to depend on small stocks. Consistent with Kaul/Nimalendran (1990), Conrad et al. (1997), and Jegadeesh/Titman (1995) for the U.S., this points to market microstructure effects, which are picked up by the results. Typically, the large return of these strategies can be explained by the bid-ask bounce. This makes the returns of these strategies illusory.

Nevertheless, in the first three 10-year sub-periods, the $r_{1,1}$ strategy produces statistically significant non-zero returns when microcap stocks are excluded (0.92%, 0.90%, 0.82%). As the sample 'excluding microcap stocks' still contains small stocks, the profitability may still be illusory. This view is supported by the statistically insignificant returns when value-weighting is applied (0.43, 0.59, 0.39). Also note that returns in the two last 10-year sub-periods – 1995 to 2004 and 2005 to 2014 – are essentially zero (-0.25 and 0.13 when equal-

[28] Based on the factor data set by Artmann/Finter/Kempf/Koch/Theissen (2012), the results are similar: 2.62% (value-weight, *t*-statistic 2.39) and 0.83% (equal-weight, *t*-statistic 1.93). Note that the factor data ends in 12/2012 and thus the calculated alphas only refer to the time period 01/2005 to 12/2012.

[29] The momentum factor is typically calculated based on the breakpoints 0.3 and 0.7, while the momentum strategies discussed here are based on the breakpoints 0.9 and 0.1 (the two extreme deciles).

weighting; -0.77 and -0.61 when value-weighting) and statistically insignificant. These findings suggest that in Germany the profitability of short-term contrarian strategies (if it ever existed) disappeared soon after Jegadeesh (1990) and Lehmann (1990) discovered them.

5.3 Seasonality Strategies

Panel C of Table 4 reports the results for seasonality strategies, which exploit the strong seasonal pattern for multiple annual lags (12, 24, 36, 48, …) discovered for the U.S. and confirmed internationally (Heston/Sadka (2008, 2010)). This strategy is denoted as r^{annual}. Based on the results obtained from Fama/MacBeth regressions in Section 4.1, it may be argued that additionally including the lags prior and next to multiple annuals lags (11 and 13, 23 and 25, 35 and 37, …) improves this strategy. This strategy is denoted as $r^{annual+}$.

Over the full period of fifty years, the r^{annual} strategy earns 1.22% when value-weighting and 0.85% when equal-weighting is applied and all stocks are considered. Much closer are the raw returns when microcap stocks are excluded from the sample (1.04% and 1.02%). The alternative strategy $r^{annual+}$ leads to returns that are similar, although typically smaller in magnitude.

When looking at the sub-periods, the final period (2005–2014) stands out from the others. While the first four 10-year sub-periods all show for both strategies in most of the cases, high and significant average raw and risk-adjusted returns, the most recent sub-period results in small and most importantly statistically insignificant returns. Only the improved $r^{annual+}$ strategy seems to earn a significant average raw (0.84%) and risk-adjusted return (0.93%, four-factor alpha) in the sample excluding microcap stocks. But this can only be found when equal-weighting is used, not in value-weight returns, which points to a small firm effect.

The findings suggest that the seasonal pattern is another anomaly that disappeared soon after its discovery. Findings from the paper of Heston/Sadka (2008) had been available from 2004, when they were first presented at major conferences. The last 10-year sub-period began in 2005, when the seasonality pattern was probably already widespread in the finance profession. I hypothesize that the seasonal pattern has also disappeared in U.S. and other international stock markets. This is supported by Keloharju/Linnainmaa/Nyberg (2015), who study various seasonality strategies: "Most seasonality strategies earn positive and statistically significant returns in all subperiods except the most recent one [2003-2011]."

5.4 Long-Term Contrarian Strategies

Panel D of Table 4 reports the results for long-term contrarian strategies. The first strategy, $r_{25,60}$, refers to the standard contrarian strategy of De Bondt/Thaler (1985, 1987), which mimics the long-term stock reversal based on the past three to five years (see also Table 3). In addition, the second strategy, $r_{13,60}$, includes the penultimate year of return history when portfolios are formed. The next two strategies are motivated by the contamination of the past two to five years performance, with the positive pulses at the multiple annual lags reported by

Heston/Sadka (2008). The $r_{13,60}^{ex\,annual}$ excludes the annual lags (24, 36, 48, 60) from the compounded return over the past 12 to 60 months. The $r_{13,60}^{ex\,annual+}$ strategy in addition excludes the previous and next lag to the multiple annual lags (13, 23-25, 35-37, 47-49, 59-60), which is motivated by the Fama-MacBeth regressions of Section 4.1 (see also Table 3 for formation).

The raw returns of the standard strategies, $r_{25,60}$ and $r_{13,60}$, are typically close to zero and statistically indistinguishable from zero in the full-period and the 10-year sub-periods. They are even significantly negative in the 1995–2004 period (e.g., -1.36%, $r_{25,60}$ with all stocks). The exclusion of microcap stocks only slightly changes the results, except for the last 10-year sub-period. The average monthly raw returns for the $r_{25,60}$ strategy drops from 2.43% (statistically insignificant) to -0.17% (statistically insignificant) when equal-weighting is applied.

The raw returns of the alternative strategies $r_{13,60}^{ex\,annual}$ and $r_{13,60}^{ex\,annual+}$ are typically a bit larger than the standard strategies. For example, the average monthly raw return is -0.25% for the $r_{25,60}$ strategy and 0.35% for the $r_{13,60}^{ex\,annual+}$ strategy (value-weighting, excluding microcap stocks). The average monthly difference between the strategies is -0.60%-points and statistically highly significant. However, the $r_{13,60}^{ex\,annual+}$ (and the strategy $r_{13,60}^{ex\,annual}$) itself only earns positive and significant returns of 0.81 (0.93) when equal-weighting is applied and all stocks are considered, but not when microcap stocks are excluded or value-weighting is used. This again points to microstructure effects and the illusory profitability of these strategies.

In total, the results suggest that all four long-term contrarian strategies are unlikely to have ever earned significantly positive average returns in Germany. This finding differs from existing German studies (see Section 2.3, literature review), which all find positive returns for long-term contrarian strategies for Germany. The difference may be down to the fact that existing studies typically calculate buy-and-hold (abnormal) returns, while my conclusions are based on (averages of monthly) calendar time portfolio returns. Hence, I mainly attribute the diverging results to methodological issues, such as the use of long-term BHAR (see Section 2.4 for a discussion) and insufficient treatment of microcap stocks.

However, note that while concluding contrarian strategies appear to be profitable, Schiereck et al. (1999) report a statistically insignificant BHAR of 21.7% after five years (*t*-statistic 1.32). Similarly, Daske (2002) reports positive and significant raw returns but cannot find risk-adjusted abnormal returns. Thus, these two papers have already indicated, more than ten years ago, that long-term contrarian strategies do not work in Germany.

The result of statistically insignificant low average monthly returns for the studied long-term contrarian strategies is also different from the U.S. stock market. Fama/French (1996) report a raw return of 0.74% (D1: 1.16%, D10: 0.42, p. 66) for the $r_{13,60}$ strategy over the time period from 1963 to 1993. For the same time period, I obtain a much lower raw return of 0.29% (*t*-statistic 1.51, all stocks) and 0.20% (*t*-statistic 1.08, excluding microcap stocks) for Germany. While Fama/French (1996) find that the reversal of long-term returns for U.S.

stocks can be explained by their three factor model, I argue that there has never been the need to explain a similar pattern in German stock returns.

6. The Triumph of Momentum Strategies?

The previous section documents that among the various strategies studied, only momentum investing appears to earn strong and persistent average stock returns. This section deepens the analysis of the momentum anomaly and investigates a few explanations. Throughout, I focus on the 3-12 momentum strategy because of the superior (although not statistically significantly larger) performance of this strategy, especially over the last ten years when compared to the 2-12 and 7-12 strategy.

6.1 Contribution of the Winner and Loser Portfolio

If the high returns of momentum strategies either fully, or to the greatest extent, result from the loser portfolio, the returns may not be exploitable because of short-selling constraints and the costs associated with lending the stocks to be sold short (Chan et al. (1996), Thomas (2006), among others). Hong et al. (2000) and Lesmond et al. (2004) find that the majority of momentum profits for the U.S. stem from the loser portfolio. Fama/French (2008) report – based on value-weight returns – for losers and winners roughly similar returns among all size classes. Based on equal-weight returns, the winner portfolio dominates the long-short investment strategy. Bromann et al. (1997) argue that momentum profits are robust to short-selling constraints in Germany. August et al. (2000) find, based on BHAR, the contribution of winner and loser portfolios to be roughly similar, with a tendency toward the winners.

The 3-12 momentum strategies purchases the 'winner' stocks (decile 10, D10) and short sells the 'loser' stocks (decile 1, D1). For Germany, over the entire time period from 1965 to 2014, I obtain the following average monthly excess returns[30] when all stocks are considered:

- Value-weighting: D1=-0.60% (*t*-statistic -1.63), D10=1.40% (*t*-statistic 5.72)
- Equal-weighting: D1= 0.09% (*t*-statistic 0.25), D10=0.94% (*t*-statistic 4.84)

And when microcap stocks are excluded, I obtain:

- Value-Weighting: D1=-0.15% (*t*-statistic -0.49), D10=1.32% (t-statistic 5.32)
- Equal-Weighting: D1=-0.57% (*t*-statistic -1.96), D10=1.05% (*t*-statistic 5.38)

The results suggest that the contribution of the loser portfolio is typically much smaller than that of the winner portfolio, e.g., with all stocks and value-weight returns the loser portfolio makes up 30% [0.60/(1.40+0.60)] and, excluding microcap stocks, only 10% [0.15/(1.32+0.15)]. While the excess returns of the loser portfolios are close to zero and insignificant (except equal-weighing excluding microcap stocks), the excess return of the winner portfolio is more than one percent per month (except equal-weighing with all stocks) and is highly statistically significant.

[30] In excess of the one-month money market rate (Monatsgeld) reported by Frankfurt banks, and after 06/2012 in excess of the one-month EURIBOR (Einmonatsgeld), see Stehle/Schmidt (2015) for details.

Figure 3: The Worth from investing €1 in the Winner, Loser and the Market

At the beginning of each month $t = 1{:}\,01/1965$ to $t = 594 = T{:}\,06/2014$ stocks are ranked according to the compounded total return over the past three to twelve months (lags). Decile portfolios are formed based on this ranking and returns are equal-weight or by the stock's market capitalization (value-weight) at the beginning of month t. In value-weight portfolios the maximum weight is limited to 50%. Decile portfolios are rebalanced monthly. A given momentum or seasonality (contrarian) strategy is short (long) in decile one and long (short) in decile ten.

The figures show the worth from investing €1 in the winner (D10, dotted line) and the loser portfolio (D1, solid line) over the total period 01/1965 to 06/2014 for the sample of all stocks and in addition for the sample excluding microcap stocks, for value-weight and equal-weight returns. The solid line with dots in the middle shows the worth from investing €1 in the market (all stocks, value-weight).

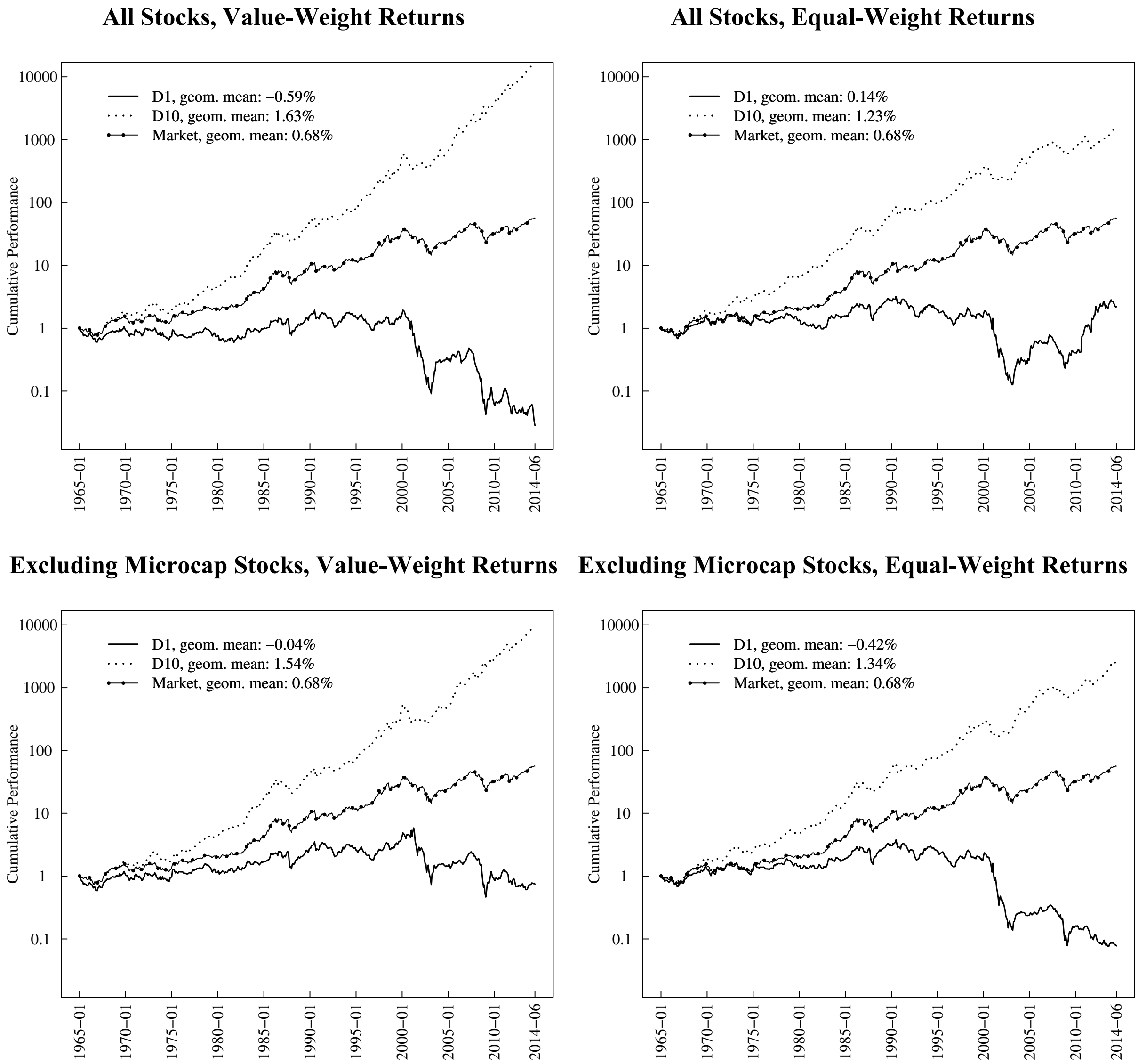


Figure 3 plots the worth from investing €1 in the winner (dotted line) and the loser portfolio (solid line) over the total time period from 1965 to 2014 for the sample of all stocks and, in addition, for the sample excluding microcap stocks for value-weight and equal-weight returns. The solid line with dots in the middle shows the worth from investing €1 in the market (all stocks, value-weight). In sum, the plots confirm that the majority of momentum profits arise from the winner portfolio. A momentum strategy that only invests in the winner portfolio and thus avoids the potential problems associated with the loser portfolio still seems to earn strong and persistent returns. These results are analogous to Bromann et al. (1997) and August et al. (2000).[31]

6.2 Size

Another concern is whether the winner and/or loser portfolio systematically contains a disproportionally large number of small stocks that are illiquid and are associated with high transaction costs, etc. Hong et al. (2000) find for the U.S., e.g., that momentum decreases with stock size. Glaser/Weber (2003) find, however, that momentum is mainly driven by stocks of medium-sized firms for Germany.

On average, one would expect to find an equal number of small, medium, and large stocks in the loser and winner portfolio. Precisely, each decile should represent on average 10% of the total market capitalization, this is, the aggregated market capitalization over all deciles. Over the entire time period from 1965 to 2014, I obtain the following average percentage of total market capitalization represented by the stocks included in the winner and loser deciles:

- D1=3.90%, D10=9.62% (all stocks),[32]
- D1=5.33%, D10=8.88% (excluding microcap stocks).[33]

The averages show that the market capitalization represented by the loser's portfolio is remarkably smaller than that of the winner's portfolio. This result is confirmed by Figure 4. The loser portfolio's size exceeds the expected 10% in only a small number of months. The figure also reveals that in the last ten years studied (2005–2014), when the average monthly raw return was remarkably high (4.42% all stocks, 2.97% excluding microcap stocks), the average market capitalization represented by the winner portfolio is also very small. This points to an important result: momentum investing relies disproportionally on small stocks. Consequently, whether the high and persistent abnormal returns of momentum strategies are actually exploitable may be called into question.

6.3 Transaction Costs

As the winner and loser portfolios largely involve trading in small stocks, the returns of momentum strategies may be offset by large transaction costs associated with these stocks. Also, since momentum strategies require frequent portfolio rebalancing, transaction costs can significantly reduce or even eliminate abnormal profits.

The only German study that takes transaction costs into account is Bromann et al. (1997), to my knowledge. They assume transaction costs of either 0.1%, 0.3%, 0.5%, or 1% for opening and closing the positions in the winner and loser portfolios. They subtract these estimates –

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31 They are also supported by Bohl et al. (2015) who argue that long-only investors earn positive and significant returns in Germany. They find that the low and typically insignificant return of the loser portfolio stems from months during market rebounds when loser stocks recover from heavy losses over preceding bear markets and exhibit large positive returns. This result, however, disappears based on a risk-adjusted basis (Fama-French three-factor model).

32 D2=6.38%, D3=8.27%, D4=9.80%, D5=11.23%, D6=11.93%, D7=12.87%, D8=13.15%, D9=12.85%.

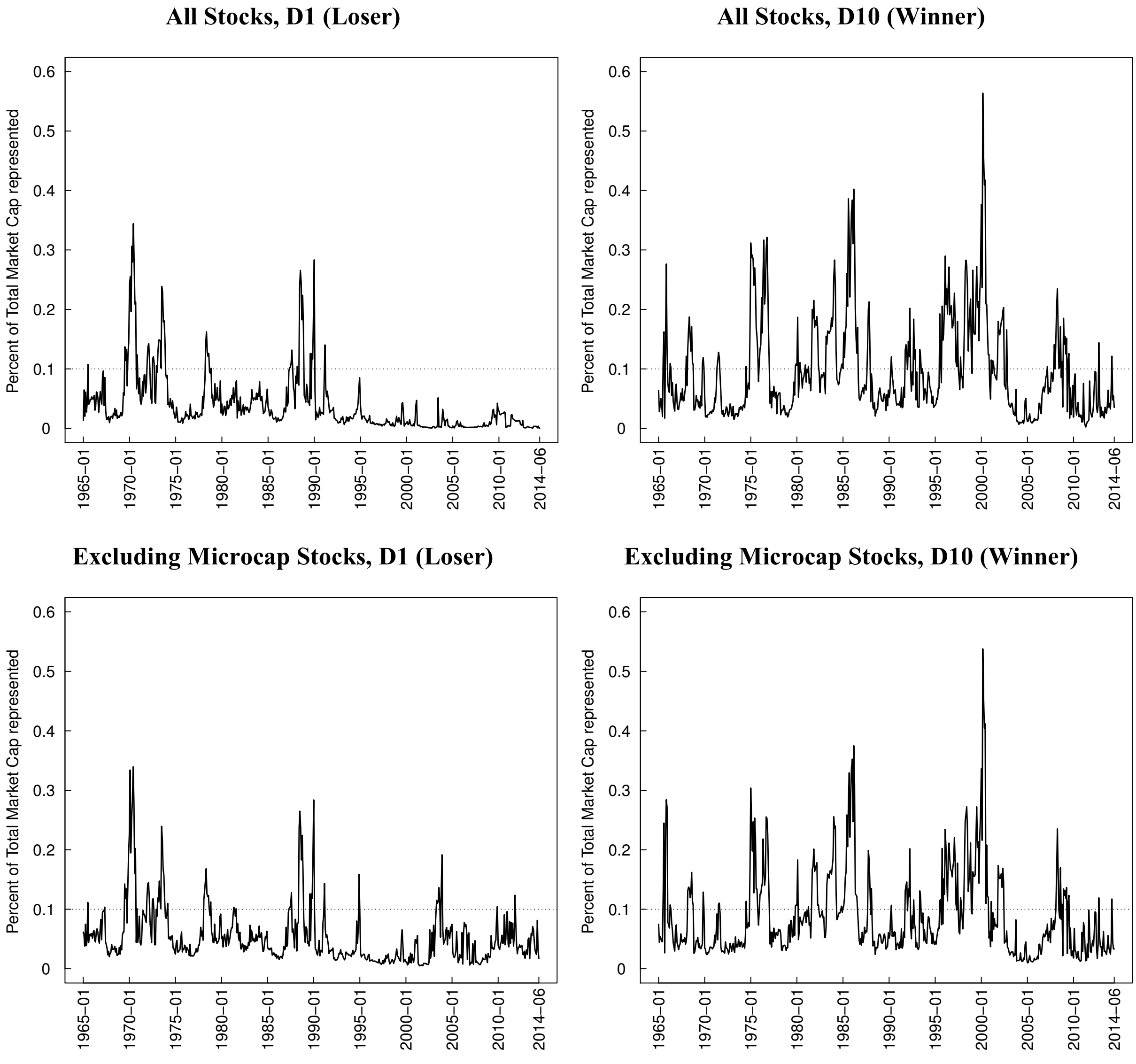
33 D2=7.94%, D3=9.85%, D4=10.63%, D5=11.03%, D6=11.22%, D7=11.85%, D8=11.49%, D9=11.77%.

four times the assumed transaction costs –[34] from the BHAR and find that only under the three smaller transaction costs estimates (0.1%, 0.3%, 0.5%) does the BHAR remain statistically significantly positive. Glaser/Weber (2003) later cast doubt on whether momentum profits survive after transaction costs but do not investigate it in detail.

Figure 4: The Percentage of Total Market Capitalization Represented by the Extreme Decile Portfolios

At the beginning of each month $t = 1{:}\,01/1965$ to $t = 594 = T{:}\,06/2014$ stocks are ranked according to the compounded total return over the past three to twelve months (lags). Decile portfolios are formed based on this ranking and returns are equal-weight or by the stock's market capitalization (value-weight) at the beginning of month t. In value-weight portfolios the maximum weight is limited to 50%. Decile portfolios are rebalanced monthly. A given momentum or seasonality (contrarian) strategy is short (long) in decile one and long (short) in decile ten.

The figures show the percentage of total market capitalization represented by the stocks included in the winner decile (D10) and the loser decile (D1) from the beginning of January 1965 to the end of June 2014. Shown are results for a sample of all stocks of all sizes and in addition for a sub-sample that excludes microcap stocks (<€50 mio, recursively adjusted by inflation, see Section 3 for details).



[34] Opening the position in the winner (1st time) and loser (2nd) portfolio at the beginning of the investment period, and closing the position in the winner (3rd) and loser (4th) portfolio at the end of the investment period.

The U.S. studies by Chen et al. (2002), Korajczyk/Sadka (2004), Lesmond et al. (2004), and Frazzini et al. (2012) do not assume static transaction costs but rather estimate them individually for stocks and typically use a battery of estimators. Chen et al. (2002) and Korajczyk/Sadka (2004) even take non-proportional costs into account, such as price impact costs, and estimate the break-even fund sizes for profitable momentum investing, which are both found to be marginally relative to the fund industry. On the other hand, Frazzini et al. (2012) use live-trading data from a large institutional investor and find momentum profits to be "robust, implementable, and sizeable".[35]

In the assessment of the profitability of momentum strategies including transaction costs, I follow Lesmond et al. (2004). That is, I first estimate trading costs according to various measures. Next, I compare the mean raw return of the winner and loser portfolios with the corresponding trading cost estimates associated with executing these portfolios. Finally, I calculate a monthly time series of net returns by subtracting the monthly trading costs estimates from the monthly time series of gross returns.

To keep the transaction costs estimate conservative, I only include the bid-ask spread and omit additional costs. This approach ignores price impact costs, which can be significant, especially when trading large volumes. However, it has the advantage of measuring marginal profitability, which is important in the context of market efficiency (Novy-Marx/Velikov (2014)).

Lesmond et al. (2004) estimate bid-ask spreads from quoted bid and ask price data, which I do as well. Lesmond et al. (2004) also use Roll's (1984) effective spread estimate and Lesmond/Ogden/Trzcinka's (1999) limited dependent variable procedure. The most recent bid-ask spread estimator proposed by Corwin/Schultz (2012) seems to dominate the older approaches including the Roll and the Lesmond/Ogden/Trzcinka estimator. I thus include the procedure of Corwin/Schultz (2012) as a second measure. Appendix C describes the procedures in detail and also presents a comparison of resulting estimates.

While momentum strategies require frequent rebalancing, not all stocks are necessarily replaced from one formation day to the next. Stocks that belong to the winner (or loser) portfolio on one formation day are also very likely to belong to the winner (or loser) portfolio on the next formation day, especially when monthly rebalancing is applied. In the 3-12 momentum strategy, one-tenth of the performance of an individual stock is replaced: for the (old) 12th monthly return, the (new) 3rd monthly past return enters the compounded return. This has implications for the calculation of the transaction costs estimates. I therefore estimate transaction costs also based on the actual turnover of the winner and loser portfolio. The details of this calculation procedure are also explained in Appendix C.

[35] Garleanu/Pederson (2013) provide a framework of optimal trading in which the net return of a strategy such as momentum could significantly improve under the presence of transaction costs.

Table 6: Transaction Costs, Gross, and Net Returns for 3-12 Momentum Strategy, 1997-2014

The table shows average monthly gross and net returns in excess of the risk-free rate for the winner (=decile 10), the loser (decile 1), and the long-short portfolio (winner minus loser) of the 3-12 momentum strategy, $r_{3,12}$, and the corresponding average monthly transaction costs estimates (=bid-ask spread estimates) for trading the portfolios. The spread estimates are based on a) quoted bid and ask data, and b) on Corwin/Schultz (2012). Shown are results for a sample of all stocks (Panel A) of all sizes and in addition for a sub-sample (Panel B) that excludes microcap stocks (<€50 mio, recursively adjusted by inflation, see Section 3 for details). Test statistics for alphas are based on Newey-West standard errors. Asterisks ***/**/* show significance at the 1/5/10% level.

		Value-Weight Returns			Equal-Weight Returns		
		Loser	Winner	W-L	Loser	Winner	W-L
Panel A: All Stocks							
I. Gross Returns	Raw	-1.02	2.21***	3.23***	0.85	1.04***	0.19
	3F-alpha	-1.58**	1.90***	3.48***	0.59	0.76***	0.17
II. Spread Estimates							
1. Based on 100% turnover							
a) Quoted Spreads		2.39	0.92	3.31	14.13	4.68	18.81
b) Corwin/Schultz		0.94	0.60	1.54	1.21	0.66	1.87
2. Based on actual turnover							
a) Quoted Spreads		1.11	0.37	1.49	4.90	1.83	6.73
b) Corwin/Schultz		0.39	0.25	0.64	0.36	0.23	0.59
III. Net Returns							
1. Based on 100% turnover							
a) Quoted Spreads	Raw	1.37	1.29**	-0.08	14.98***	-3.64***	-18.62***
	3F-alpha	0.80	0.98*	0.18	14.56***	-3.96***	-18.53***
b) Corwin/Schultz	Raw	-0.08	1.61***	1.69*	2.06**	0.38	-1.67**
	3F-alpha	-0.64	1.29**	1.93**	1.79**	0.09	-1.70**
2. Based on actual turnover							
a) Quoted Spreads	Raw	0.09	1.84***	1.75*	5.75***	-0.79**	-6.54***
	3F-alpha	-0.49	1.53***	2.01**	5.40***	-1.07***	-6.48***
b) Corwin/Schultz	Raw	-0.63	1.97***	2.60***	1.21	0.81**	-0.40
	3F-alpha	-1.20*	1.65***	2.85***	0.95	0.53*	-0.42
Panel B: Excluding Microcap Stocks							
I. Gross Returns	Raw	-0.09	2.06***	2.14***	-1.10	1.47***	2.57***
	3F-alpha	-0.76	1.81***	2.57***	-1.39***	1.15***	2.54***
II. Spread Estimates							
1. Based on 100% turnover							
a) Quoted Spreads		1.20	0.86	2.06	2.47	1.84	4.31
b) Corwin/Schultz		0.75	0.59	1.34	0.76	0.56	1.33
2. Based on actual turnover							
a) Quoted Spreads		0.53	0.33	0.86	0.87	0.61	1.48
b) Corwin/Schultz		0.32	0.23	0.56	0.25	0.18	0.43
III. Net Returns							
1. Based on 100% turnover							
a) Quoted Spreads	Raw	1.11	1.19**	0.08	1.36**	-0.37	-1.73***
	3F-alpha	0.45	0.95*	0.50	1.07***	-0.69**	-1.76***
b) Corwin/Schultz	Raw	0.67	1.47***	0.80	-0.34	0.91**	1.25**
	3F-alpha	0.01	1.22**	1.21	-0.62*	0.58*	1.21**
2. Based on actual turnover							
a) Quoted Spreads	Raw	0.45	1.73***	1.28	-0.23	0.86**	1.09*
	3F-alpha	-0.22	1.48***	1.70*	-0.52	0.54*	1.06**
b) Corwin/Schultz	Raw	0.24	1.82***	1.59**	-0.86	1.29***	2.15***
	3F-alpha	-0.43	1.58***	2.01**	-1.14***	0.97***	2.11***

Table 6 shows the gross and net returns for the winner, loser, and long-short portfolio (winner minus loser) along with the transaction costs estimates for executing these portfolios. Presented are time series averages for the time period from 01/1997 to 06/2014.[36] Average monthly gross and net returns are in excess of the risk-free rate (source: see Footnote 30) to make the returns to the loser or winner portfolio comparable to the long-short portfolio. (The long-short portfolio has a net investment of zero; the stocks purchased are financed by the stocks that are short-sold. The pure investment in the winner portfolio, e.g., could be financed at the risk-free rate.) Since I find the Corwin/Schultz measure to be inappropriate for estimating bid-ask spreads for German smallcap stocks, I base my conclusions on the quoted spread measure (see Appendix C for details). However, because I will also focus on value-weight returns, which puts less weight on small stocks that may be difficult to trade, the results based on the Corwin/Schultz measure and the quoted spread measure are very similar.

Panel A shows the results for when all stocks are included. Similar to the total 60-year time period, the average monthly gross return of the winner portfolio is positive and statistically significant for both value-weight (2.21%) and equal-weight returns (1.04%). The gross return of the loser portfolios also follow the pattern of what is observed over the total 60-year time period: negative when value-weighting (-1.02%), positive when equal-weighting (0.85%), and both statistically insignificant. The average monthly transaction costs estimates obtained for the winner portfolios are much smaller than they are for the loser portfolios. Trading the value-weight loser portfolio is associated with 2.39%, the value-weight winner portfolio with *only* 0.92% when based on quoted spreads and 100% turnover. The high transaction costs for the loser portfolio confirms that this portfolio typically involves trading a large number of very small stocks that are associated with high transaction costs. Due to the high transaction costs of the loser portfolio, the average monthly net return earned from this portfolio is positive (1.37%, though negative because it requires going short in this position). On average, the loser portfolio does not positively contribute to the long-short portfolio. Also, based on actual turnover and the quoted spread measure, the average monthly net return is 0.09%, and statistically insignificant. The risk-adjusted net return (three-factor alpha) is -0.49, but statistically insignificant. The winner portfolio, on the other hand, is only associated with average transaction costs of 0.37% when based on the actual turnover. The net return is 1.84% (2.21% gross minus 0.37%) and statistically significant. The risk-adjusted net return is only slightly smaller: 1.53% and again statistically significant.

Panel B shows the results when microcap stocks are excluded from the sample. Similar to the analysis that includes all stocks, the loser portfolio is associated with much larger transaction costs. They are 1.20% based on the quoted spread measure, and 0.75% based on the Corwin/Schultz measure (100% turnover). The winner portfolio, in turn, is *only* associated with 0.86% or 0.59%. Both estimates are, as expected, lower than in the analysis that includes all stocks. Even lower are the transaction costs estimates based on the actual turnover. For the

[36] Data limitations allow to investigate only the time period 1997 to 2014, see Appendix C.

loser and winner portfolio both measures are between 0.53% and 0.23%. As the average monthly gross return of the loser portfolio is only -0.09, the net return is positive: 0.45% (-0.09% gross plus 0.53%, the cost for trading the loser portfolio based on actual turnover). This result is equivalent to the analysis that includes all stocks and shows that the loser portfolio on average cannot positively contribute to the long-short portfolio. The alphas obtained from the three-factor model are positive when based on 100% turnover and negative when based on actual turnover. However, all are statistically insignificant.

The winner portfolio has an average monthly gross return of 2.06% that turns into a net return of 1.73% (2.06%-0.33%) based on actual turnover. This result is robust with respect to the spread measure used, and also when based on 100% turnover. The three-factor alphas are lower than the raw returns, but are still highly economically and statistically significant. The long-short portfolio has a risk-adjusted net return (alpha=1.70, quoted spread based on actual turnover) that is larger than those of the winner portfolio. This results from the loser portfolio, which adds to the long-short portfolio on a risk-adjusted basis (1.48-[-0.22]=1.70). However, the higher risk-adjusted return of the long-short portfolios comes with a decrease in statistical significance: the 1.70 is only significant on the 10% level (*t*-statistic 1.94), while the 1.48 of the winner portfolio is significant on the 1% level (*t*-statistic 2.73).

Overall, generating robust and persistent trading profits from the 3-12 momentum strategy net of transaction costs appears weak, especially in the view of the conservative transaction costs estimates which *only* include the bid-ask spread. On the other hand, the results suggest that trading only the winner portfolio is rewarded with high, robust, and persistent returns, even after transaction costs. This result does not change based on a risk-adjusted basis.

7. Conclusion

This paper highlights the need to carefully develop an adequate research design when studying the German stock market. The selection of an appropriate sample appears very important. In the last fifteen years, the German stock market contained a large amount of micro- and smallcap stocks, much more than in the time period before. This may not only be important for the various investment strategies examined in this paper, but also for other empirical papers on the returns of German stocks. When considering this, I find it appropriate to distinguish between two samples; one that includes all stocks, and one that excludes stocks based on an inflation adjusted €-limit rather than on a fixed percentile in market capitalization.

In addition, I argue that the use of value-weight returns instead of equal-weight returns is essential in the assessment of the profitability of the various strategies. To my knowledge, all existing German studies on the returns of momentum and contrarian strategies only use equal-weight returns in their portfolios. A strategy that promises large average returns based on equal-weight returns in combination with a sample that is dominated by small stocks may not be profitable for investors due to transaction costs, illiquidity, etc. My results document that the use of value-weight returns is essential when asking whether the discussed strategies earn robust and persistent returns.

There are many results documented for the U.S., which I confirm for the German stock market (such as the high average returns for short-term contrarian strategies that concentrate in microcap stocks). However, there are also a few exceptions, which highlight the need to pursue research in international capital markets. The large and robust return of the winner portfolio in the momentum strategy, in particular, is puzzling and much higher than in the U.S, which opens the door for further investigation.

Appendix A: Fama-MacBeth Regressions with Single and/or Compounded Returns over Certain Contiguous and Non-Contiguous Past Horizons

To further explore whether certain lags contribute to a given strategy, I run multivariate Fama/MacBeth (1973) cross-sectional regressions by including (1) single lagged returns and/or (2) compounded returns over certain contiguous and non-contiguous past horizons as explanatory variables. The compounded and single returns over certain past horizons are selected on the basis of the results reported in Table 2. Specifically, included are

i) single lagged returns (e.g. lag 1),
ii) compounded (contiguous) lagged returns (e.g. lag 5-12),
iii) multiple Cumulative (non-contiguous) lagged returns (e.g. lag 13-23 plus 25-35 plus 37-47 plus 49-59, which in fact is lag 13-60, excluding the annual lags 24, 36, 48, 60), and
iv) annual Cumulative (non-contiguous) lagged returns (e.g. lag 12 plus 24 plus 36 plus 48 plus 60).

Table A. 1: Multivariate Fama-MacBeth Regression Results

This table shows the results from multivariate Fama-MacBeth regressions with multiple combinations of lagged returns. The regression is estimated in month $t = 1{:}\,01/1965$ to $t = 594 = T{:}\,06/2014$. The coefficients are multiplied by 10^2. Asterisks ***/**/* show significance at the 1/5/10% level.

	A.I	A.II	A.III	A.IV	A.V	A.VI	B.I	B.II
Intercept	0.86***	0.82***	0.77***	1.00***	0.98***	0.89***	0.95***	0.96***
	(4.95)	*(5.16)*	*(4.75)*	*(6.44)*	*(6.18)*	*(5.84)*	*(6.58)*	*(6.40)*
Lag 1	-4.24***						-5.45***	-5.17***
	(-5.48)						*(-7.18)*	*(-6.61)*
Lag 2	-0.42	-0.56	-0.32				-1.04*	
	(-0.71)	*(-0.93)*	*(-0.54)*				*(-1.72)*	
Lag 3		0.84*					0.26	
		(1.66)					*(0.52)*	
Lag 4		0.62					0.49	
		(1.08)					*(0.88)*	
Lag 5-12		1.06***					0.94***	
		(4.57)					*(4.28)*	
Lag 3-12			0.98***					0.85***
			(4.38)					*(4.05)*
Lag 14-22, 26-34, 38-46, 50-58				-0.30***			-0.32***	-0.34***
				(-4.05)			*(-4.60)*	*(-4.75)*
Lag 13, 23, 25, 35, 37, 47, 49, 59				0.24			0.35**	
				(1.58)			*(2.46)*	
Lag 24, 36, 48, 60				1.11***	1.10***		1.10***	1.18***
				(5.54)	*(5.41)*		*(5.71)*	*(6.00)*
Lag 13-23, 25-35, 37-47, 49-59					-0.23***			
					(-3.28)			
Lag 11, 13, 23, 25, 35, 37, 47, 49, 59						0.31**		
						(2.08)		
Lag 12, 24, 36, 48, 60						1.40***		
						(6.58)		

Table A. 1 shows the results for multiple setups. In the first setup (A.I), the insignificant average coefficient for the second lag indicates that a short-term contrarian strategy does not improve by including this lag. Thus, the results reported in Table 2, which suggested the opposite, are not robust in this respect. For a momentum strategy, it seems to be useful not only to include the lags five to twelve, but also the third lag because of the positive and significant coefficient for lag three. Excluding the second lag seems not to significantly improve the strategy.

Setup A.IV and A.V support the results of Table 2: a long-run contrarian strategy seem to improve by excluding the multiple annual lags. The average coefficient for the multiple compounded lagged return (lag 14-22, 26-34, 38-46, 50-58) is negative (-0.30) and highly statistically significant (*t*-statistic -4.05), while the average coefficient for the annual compounded lagged return (lag 12, 24, 36, 48, 60) is positive (1.11) and highly statistically significant (*t*-statistic 5.54). Table A. 1 also supports the results of Table 2 with respect to the improvements that could be made to the portfolio strategy proposed Heston/Sadka (2008). The coefficient in column seven is positive (0.31) and statistically significant (*t*-statistic 2.08) for the previous and next lag to the multiple annual lags (lag 11, 13, 23, 25, 35, 37, 47, 49, 59).

Appendix B: Additional Descriptive Statistics

Table A. 2: Descriptive Statistics of Momentum, Contrarian, and Seasonality Strategies, 1965-2014

Strategy		Min	0.25	Median	0.75	Max	Mean	Sd	Kurt	Skew
Panel A: Value-Weight Returns										
Sample: All										
Short-Term Contrarian	$r_{1,1}$	-65.47	-3.49	0.09	3.36	59.42	0.02	7.88	20.47	0.15
	$r_{1,2}$	-66.31	-3.47	0.11	3.16	53.45	-0.16	7.82	18.05	-0.07
Momentum	$r_{2,12}$	-49.47	-1.99	1.66	5.22	65.88	1.76	8.96	12.13	0.21
	$r_{3,12}$	-47.01	-2.09	1.48	5.63	67.35	2.00	8.99	12.02	0.37
	$r_{7,12}$	-49.35	-2.29	1.40	4.61	48.95	1.22	7.71	13.13	-0.77
Long-Term Contrarian	$r_{25,60}$	-31.69	-3.46	-0.25	2.79	33.47	-0.15	6.16	7.41	0.45
	$r_{13,60}$	-35.08	-3.72	-0.47	2.57	80.09	-0.09	7.37	29.39	2.69
	$r_{13,60}^{ex\ annual}$	-35.85	-3.52	0.07	3.13	82.40	0.08	7.08	35.17	2.76
	$r_{13,60}^{ex\ annual+}$	-34.99	-3.14	-0.13	3.22	88.25	0.25	7.42	39.55	2.95
Seasonality	r^{annual}	-26.35	-1.78	1.11	4.02	55.44	1.22	5.71	18.35	1.25
	$r^{annual+}$	-56.60	-1.65	1.13	4.09	34.60	1.07	6.37	16.53	-1.21
Sample: Excluding Microcap Stocks										
Short-Term Contrarian	$r_{1,1}$	-62.38	-2.66	0.03	3.25	37.13	0.01	6.96	19.47	-0.86
	$r_{1,2}$	-65.42	-3.15	-0.01	2.98	46.05	-0.13	7.02	21.02	-0.58
Momentum	$r_{2,12}$	-53.33	-2.00	1.39	4.92	66.69	1.57	8.48	15.20	0.21
	$r_{3,12}$	-44.14	-2.44	1.40	4.66	65.89	1.48	7.85	14.61	0.81
	$r_{7,12}$	-40.96	-1.80	1.27	4.11	62.34	1.35	7.05	16.80	0.30
Long-Term Contrarian	$r_{25,60}$	-23.87	-3.09	-0.22	2.66	18.13	-0.25	5.11	4.59	-0.09
	$r_{13,60}$	-23.66	-3.15	-0.07	2.81	47.90	0.09	5.72	11.89	1.08
	$r_{13,60}^{ex\ annual}$	-20.24	-2.70	0.20	3.18	46.36	0.41	5.58	11.39	1.19
	$r_{13,60}^{ex\ annual+}$	-29.76	-2.61	0.22	3.57	22.38	0.35	5.45	6.36	-0.16
Seasonality	r^{annual}	-32.83	-1.89	0.93	3.53	47.18	1.04	5.61	14.53	0.69
	$r^{annual+}$	-47.22	-1.46	0.84	3.83	17.73	0.84	5.30	16.03	-1.72
Panel B: Equal-Weigth Returns										
Sample: All										
Short-Term Contrarian	$r_{1,1}$	-29.17	-1.61	1.11	4.00	74.30	1.93	7.58	24.35	3.00
	$r_{1,2}$	-56.87	-1.89	0.61	3.98	73.60	1.61	8.61	24.30	2.04
Momentum	$r_{2,12}$	-83.70	-1.75	1.32	4.33	30.09	0.77	8.12	30.64	-3.20
	$r_{3,12}$	-67.87	-1.66	1.33	4.22	29.12	0.85	7.55	23.68	-2.61
	$r_{7,12}$	-94.00	-1.48	1.07	3.61	55.38	0.63	7.89	49.65	-3.79
Long-Term Contrarian	$r_{25,60}$	-16.02	-2.54	-0.16	2.36	117.39	0.58	7.84	101.04	7.84
	$r_{13,60}$	-13.77	-2.71	-0.34	2.26	118.51	0.49	8.18	94.37	7.52
	$r_{13,60}^{ex\ annual}$	-13.55	-2.60	0.07	2.73	113.42	0.81	7.88	89.61	7.24
	$r_{13,60}^{ex\ annual+}$	-13.65	-2.18	0.31	2.82	121.57	0.93	7.91	108.00	8.07
Seasonality	r^{annual}	-71.12	-1.00	0.91	3.31	19.56	0.85	5.48	59.55	-4.96
	$r^{annual+}$	-72.58	-1.09	1.01	3.38	15.31	0.68	6.33	63.50	-5.76
Sample: Excluding Microcap Stocks										
Short-Term Contrarian	$r_{1,1}$	-35.61	-1.91	0.63	2.82	42.29	0.51	5.47	14.76	0.70
	$r_{1,2}$	-44.11	-2.41	0.20	2.55	36.73	0.01	5.95	14.50	-0.06
Momentum	$r_{2,12}$	-31.32	-1.05	1.59	4.44	29.07	1.70	6.00	9.25	-0.33
	$r_{3,12}$	-31.21	-1.02	1.39	4.37	28.76	1.62	5.80	8.76	-0.35
	$r_{7,12}$	-25.90	-1.12	1.42	3.99	19.93	1.43	4.79	7.46	-0.42
Long-Term Contrarian	$r_{25,60}$	-12.24	-2.26	-0.16	2.01	13.17	-0.01	3.62	4.07	0.22
	$r_{13,60}$	-11.76	-2.52	-0.20	2.08	13.20	-0.13	3.90	3.70	0.17
	$r_{13,60}^{ex\ annual}$	-12.06	-2.08	0.05	2.25	16.51	0.19	3.90	4.10	0.35
	$r_{13,60}^{ex\ annual+}$	-14.42	-2.10	0.20	2.62	16.62	0.28	3.79	4.21	0.24
Seasonality	r^{annual}	-13.34	-0.96	0.99	2.97	17.12	1.02	3.39	4.53	0.11
	$r^{annual+}$	-15.45	-1.11	0.94	3.20	17.17	0.98	3.56	4.78	-0.06

Appendix C: Bid-Ask Spread Estimation Procedure and Comparison of Estimates

Quoted Spread Procedure

Based on Stoll/Whaley (1983) and following Lesmond et al. (2004), I obtain bid-ask spread estimates based on quoted bid and ask prices. Estimates are calculated individually for each stock, based on daily closing bid and ask quotes obtained from Datastream. The spread is estimated over Frankfurt Stock Exchange trading day $d-15$ to $d-6$ (=two weeks), relative to portfolio formation to mitigate any influence of turn-of-the-month effects in quotes (Lesmond et al. (2004)). The quoted spread measure for stock i at the beginning of month t is

$$Quoted\ Spread_{i,t} = \frac{1}{10}\sum_{\tau=-15}^{-6}\frac{a_{i,d+\tau}-b_{i,d+\tau}}{\frac{1}{2}\left(a_{i,d+\tau}+b_{i,d+\tau}\right)} \tag{3}$$

with $a_{i,d+\tau}$ the quoted ask price, $b_{i,d+\tau}$ the quoted bid price on day d for stock i.

Corwin/Schultz Procedure

Bid-ask spread estimates based on Corwin/Schultz (2012) are also estimated over Frankfurt Stock Exchange trading day $d-15$ to $d-6$ (=two weeks) relative to portfolio formation. Based on daily high and low prices, the Corwin/Schultz measure for stock i in at the beginning of month t is

$$CS\ Spread_{i,t} = \frac{1}{10}\sum_{\tau=-15}^{-6} max\left(\frac{2(e^{\alpha_{i,d+\tau}}-1)}{1+e^{\alpha_{i,d+\tau}}}, 0\right) \tag{4}$$

with

$$\alpha_{i,d} = \frac{\sqrt{2\beta_{i,d}}-\sqrt{\beta_{i,d}}}{3-2\sqrt{2}} - \sqrt{\frac{\gamma_{i,d}}{3-2\sqrt{2}}} \tag{5}$$

where

$$\beta_{i,d} = \left[ln\left(\frac{P_{i,d}^{H,adj}}{P_{i,d}^{L,adj}}\right)\right]^2 + \left[ln\left(\frac{P_{i,d-1}^{H}}{P_{i,d-1}^{L}}\right)\right]^2 \tag{6}$$

and

$$\gamma_{i,d} = \left[ln\left(\frac{max\left(P_{i,d-1}^{H}, P_{i,d}^{H,adj}\right)}{min\left(P_{i,d-1}^{L}, P_{i,d}^{L,adj}\right)}\right)\right]^2. \tag{7}$$

$P^H_{i,d}$ and $P^L_{i,d}$ are the high and low price, $P^{H,adj}_{i,d} = P^H_{i,d} - \Delta PON$ and $P^{L,adj}_{i,d} = P^L_{i,d} - \Delta PON$ are the high and low adjusted price with $\Delta PON = \max\ \left(P^L_{i,d} - P^C_{i,d-1}, 0\right) + \max\ \left(P^C_{i,d-1} - \right.$ $Pi,dH,0$, the estimated overnight price change with Pi,dC the closing price of stock i on Frankfurt Stock Exchange trading day d. Thus, I make use of the overnight return adjustment described in Corwin/Schultz (2012).

Spread Estimates Based on Actual Turnover

All strategies are studied with monthly rebalancing throughout this paper.[37] When incorporating transaction costs, it should be taken into account that, typically, not all stocks in the winner and/or loser portfolio are replaced every month. Hence, the stock positions that can be kept are not associated with transaction costs.

To incorporate the fact that the weight of a stock in a portfolio at the beginning of a month is typically different to the weight at the end,[38] I first calculate for each stock i in a given portfolio the end of month t portfolio weight:

$$w^{End}_{i,t} = \frac{w^{Start}_{i,t}\left(1 + r_{i,t}\right)}{\sum_{i=1}^{N} w^{Start}_{i,t}\left(1 + r_{i,t}\right)} \tag{8}$$

with $w^{Start}_{i,t}$ the beginning of month portfolio weight of stock i, which is the weight (equal- or value-weight) obtained based on the portfolio formation described in Section 4.2.

The difference between $w^{Start}_{i,t}$ and the end of month weight of $t-1$, $w^{End}_{i,t-1}$, is the change in a stock's portfolio weight, due to the new weights obtained from the formation ($w^{End}_{i,0} = 0$). I assume that all transaction costs accrue when a stock position is opened, which in turn implies that only additional stock positions are subjected to trading costs. Thus, the proportion of stock holdings of stock i in a given portfolio that is associated with additional transaction costs is

$$\Delta p_{i,t} = \begin{cases} 0 & if\ w^{Start}_{i,t} = 0 \\ max\left(\dfrac{w^{Start}_{i,t} - w^{End}_{i,t-1}}{w^{Start}_{i,t}}, 0\right) & else \end{cases} \tag{9}$$

with $0 \leq p \leq 1$. The quoted spread measure adjusted for actual turnover is in turn

$$Quoted\ Spread^{act}_{i,t} = QS_{i,t}\Delta p_{i,t}, \tag{10}$$

[37] Appendix D, however, contains results for holding periods of longer than one month, this is rebalancing after e.g. three, six or twelve months.

[38] E.g., at the beginning of a month five stocks are sorted into a portfolio with each having a weight of 20%. During the month, one stock gained 30% all other 0%. At the end of the month the portfolio weights are (20*1.3)/(20+20+20+20+(20*1.3)=26/106=24.53% for the stock that gained 30% during the month, and all other nine stocks have a weight of 20/(20+20+20+20+(20*1.3))=20/106=18.87%.

and for the Corwin/Schultz measure

$$CS\ Spread_{i,t}^{act} = CS_{i,t}\Delta p_{i,t}. \tag{11}$$

Comparison of Bid-Ask Spread Estimates

Datastream offers bid and ask quotes for the German stock market from end of 1996 onwards, which enables me to estimate the quoted spread measure from January 1997 onwards. Daily high, low and closing prices are available for most of the stocks in the sample from September 1988 onwards. Because Brückner (2012) does not recommend German stock market data from Datastream before 1990, I only calculate the Corwin/Schultz measure from January 1990 onwards. Thus, I am able to assess the profitability of momentum strategies net of bid-ask spread over the time period from 1990 to 2014 by using the Corwin/Schultz measure, and over the time period from 1997 to 2014, also based on the quoted spread measure.

Figure A. 1 shows the average estimates of bid-ask spreads for size quintiles based on all stocks in the sample.[39] The four plots altogether are based on 126,384 individual estimates (stock-months) for the quoted bid-ask spread beginning in January 1997, and 157,976 estimates for the Corwin/Schultz measure beginning in January 1990. The first plot shows the average bid-ask spread estimates for the largest stocks in the sample (Q5). Both lines are close to each other and indicate that the two measures produce similar results although the average estimates obtained from the quoted bid and ask data are generally higher. Within the size quintiles containing medium-sized stocks (Q4, Q3, Q2), the bid-ask spread estimates are not as close. While the quoted bid-ask spread estimates increase with decreasing stock size, the estimates based on Corwin/Schultz change only marginally. Among the stocks that are smallest in size, the difference between both lines is remarkably: the spreads based on the Corwin/Schultz measure is flat and close to zero, the bid-ask measure based on quoted prices reaches average estimates of 10% around the turn of the millennium and up to 30 to 50% after 2008 (note the bandwidth of the y-axis).

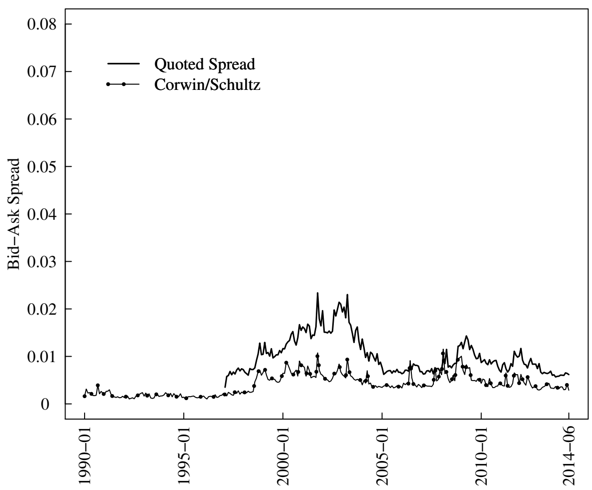
For the quintile containing the smallest stocks (Q1), the estimates based on quoted bid and ask prices appear to be odd, especially for the most recent time period. This again highlights the need to carefully select an adequate sample of stocks and/or use alternative weighting schemes such as value-weighting. For the other quintiles, the time-series and cross-sectional variation of the average estimates appear to be reasonable.

[39] I note that including all stocks ignores the large increase in the number of small and microcap stocks after 2000, which I stress in Section 3. As a consequence, the breakpoints largely change after 2000 and thus the allocation of the stocks to the quintiles. However, for a direct comparison of the estimates obtained from the two bid-ask spread measures it is of minor importance.

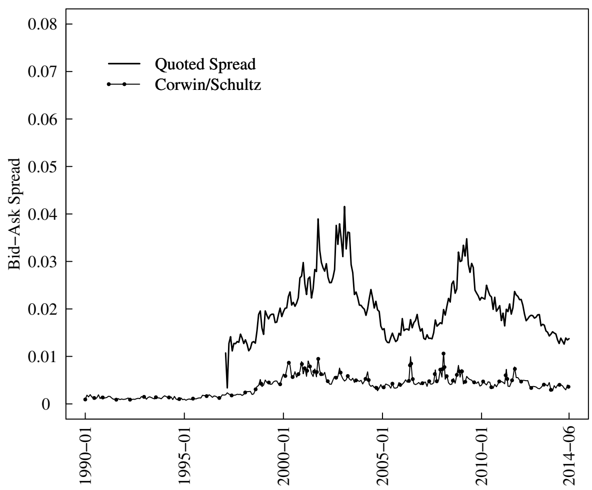
Figure A. 1: Average Bid-Ask Spread Estimates for Size Quintiles

At the beginning of each month between 01/1990 and 06/2014 for each stock in the sample (no exclusions) a bid-ask spread estimate is obtained based on Corwin/Schultz (2012) and quoted bid and ask prices, see the formulas in Appendix C. The figure shows the average spread estimates for size quintiles over time.

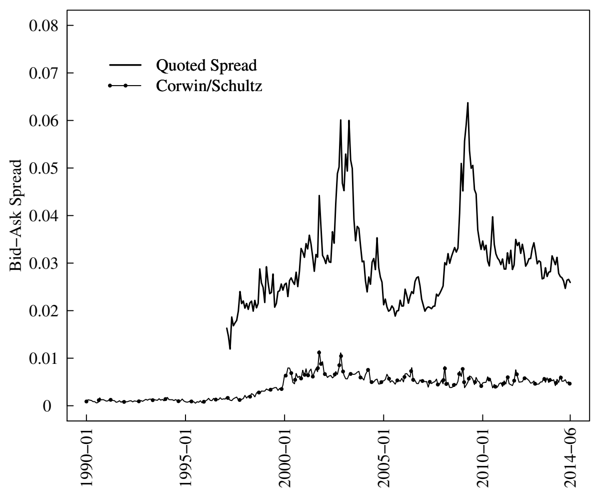
Q5 (Largest in Size)



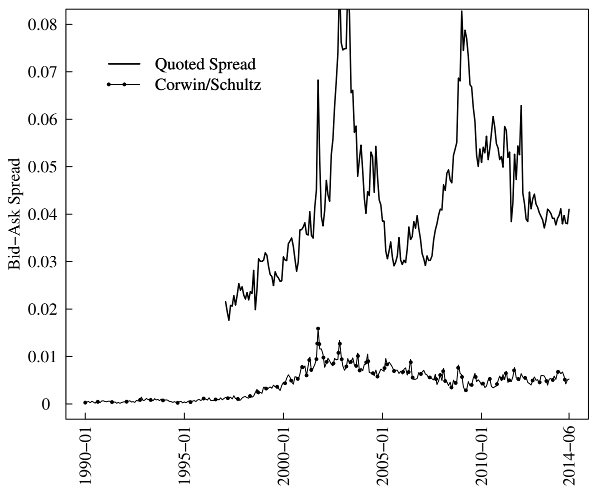
Q4



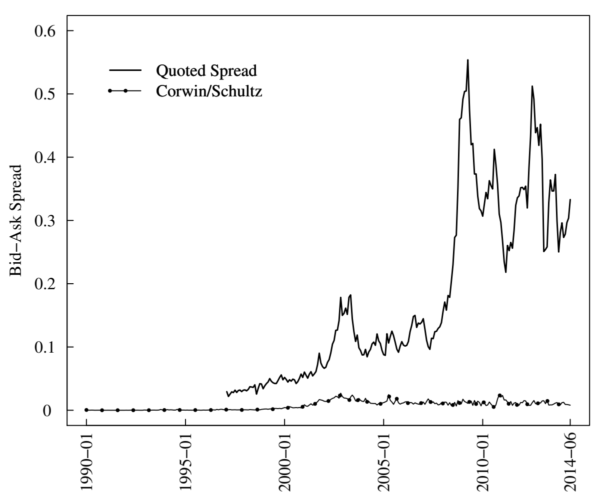
Q3



Q2



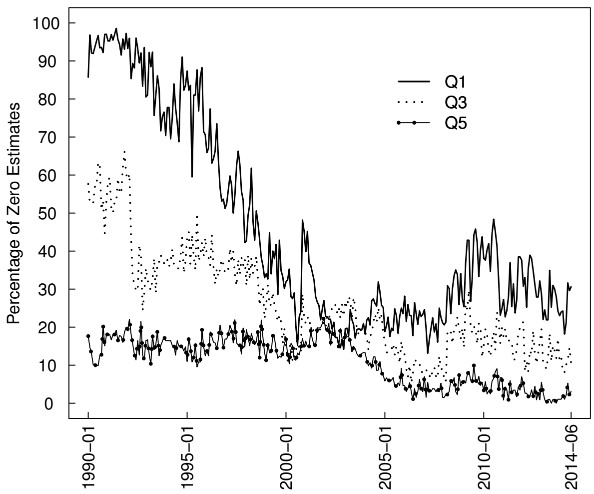
Q1 (Smallest in Size)



On the other hand, the very limited time-series and cross-sectional variation in the average estimates based on Corwin/Schultz is less satisfying. A thorough analysis of the individual estimates reveals that many are zero (actually negative and forced to zero, see formula 4). Between 1990 and 1996, about 47.5% of the individual estimates are zero. Between 1997 and 2014, about 19.4% are zero. As Corwin/Schultz (2012) point out (p. 727), the individual spread estimates on single days can be zero. In fact, in a number of cases all ten individual daily estimates are zero, and thus the average. Figure A. 2 shows that the number of zero estimates largely diverges among the size quintiles: with decreasing stock size, the number of zero estimates increases. This is the reason why the Corwin/Schultz estimates largely diverge from the quoted spread estimates in the mid- and small-sized quintiles. In sum, based on the available data from Datastream and in the context of this paper, I find the Corwin/Schultz measure to be inappropriate for estimating bid-ask spreads for German smallcap stocks.

Figure A. 2: Percentage of Zero Bid-Ask Spread Estimates for Size-Quintiles based on Corwin/Schultz

At the beginning of each month between 01/1990 and 06/2014 for each stock in the sample a bid-ask spread estimate based on Corwin/Schultz (2012) is obtained, see the formulas in Appendix C. The figure shows the average percentage of zero estimates for three size quintiles (the smallest, Q1; the largest, Q5; and the medium-sized stocks, Q3) over time.



Appendix D: Alternative Holding Periods (rebalancing every 3, 6, 12 months)

Table A. 3: Returns on Various Strategies, Rebalancing Every Three Month

At the beginning of each third month $t = 1{:}\,01/1965$ to $t = 594 = T{:}\,06/2014$ stocks are ranked according to the compounded total return over specific contiguous and non-contiguous lags (see Table 3 for details). Decile portfolios are formed based on this ranking and returns are equal-weight or by the stock's market capitalization (value-weight) at the beginning of month t. In value-weight portfolios the maximum weight is limited to 50%. Thus, decile portfolios are rebalanced every three months. A given momentum or seasonality (contrarian) strategy is short (long) in decile one and long (short) in decile ten.

Presented are average monthly raw returns and alphas obtained from one factor (Jensen (1968)), three factor (Fama/French (1993)) and four factor (Carhart (1997)) regressions. Shown are results for a sample of all stocks of all sizes and in addition for a sub-sample that excludes microcap stocks (<€50 mio, recursively adjusted by inflation, see Section 3 for details). Test statistics for alphas are based on Newey-West standard errors. Asterisks ***, **, * signal a significance level of 1%, 5%, and 10%.

	Value-Weight Returns						Equal-Weight Returns					
	Full Period	10 year Sub Periods					Full Period	10 year Sub Periods				
	1965 - 2014	1965 - 1974	1975 - 1984	1985 - 1994	1995 - 2004	2005 - 2014	1965 - 2014	1965 - 1974	1975 - 1984	1985 - 1994	1995 - 2004	2005 - 2014
Panel A: Momentum												
$r_{2,12}$												
Sample: All												
Raw	1.54***	0.42	1.30***	0.72	2.06*	3.29***	0.69**	0.68*	1.25***	1.15***	2.13**	-1.90
1F-alpha	1.65***	0.36	1.30***	0.73	2.19*	3.97***	0.83***	0.61	1.28***	1.22***	2.32***	-1.36
3F-alpha	1.74***	0.36	1.31***	0.48	1.20	4.62***	0.74**	0.67	1.28***	1.08***	1.29	-1.33
4F-alpha	0.37	0.22	0.35	-0.01	-0.79	1.91**	0.00	0.54	0.58*	0.68**	0.01	-1.95**
Sample: Excluding Microcap Stocks												
Raw	1.31***	0.51	1.41***	0.88*	1.80*	1.98*	1.59***	0.46	1.16***	1.13***	3.24***	1.98***
1F-alpha	1.42***	0.46	1.39***	0.90*	1.88*	2.67**	1.71***	0.39	1.14***	1.19***	3.46***	2.37***
3F-alpha	1.51***	0.44	1.40***	0.64	1.08	3.45***	1.60***	0.32	1.14***	0.99**	2.65***	2.56***
4F-alpha	0.14	0.28	0.57*	0.19	-1.01	0.70	0.65***	0.18	0.32	0.58**	1.12**	1.23**
$r_{3,12}$												
Sample: All												
Raw	1.32***	0.37	1.20***	0.87*	1.22	3.05**	0.62**	0.60	1.33***	1.11***	1.48*	-1.55
1F-alpha	1.43***	0.31	1.19***	0.90*	1.29	3.72***	0.73***	0.53	1.33***	1.15***	1.63*	-1.05
3F-alpha	1.55***	0.28	1.19***	0.73	0.26	4.50***	0.66**	0.63*	1.33***	1.05***	0.62	-1.07
4F-alpha	0.29	0.11	0.43	0.30	-1.47	1.85**	-0.03	0.48	0.66**	0.66**	-0.50	-1.65*
Sample: Excluding Microcap Stocks												
Raw	1.08***	0.38	1.29***	0.75	0.95	2.10*	1.39***	0.37	1.07***	1.06***	2.45***	2.02***
1F-alpha	1.19***	0.31	1.27***	0.75	1.06	2.68**	1.50***	0.30	1.07***	1.09***	2.65***	2.38***
3F-alpha	1.29***	0.28	1.27***	0.58	0.50	3.48***	1.41***	0.27	1.07***	0.96**	1.89**	2.62***
4F-alpha	0.01	0.12	0.47	0.16	-1.42*	0.79	0.51***	0.14	0.30	0.56*	0.50	1.27***
$r_{7,12}$												
Sample: All												
Raw	0.98***	0.32	1.20***	0.94**	1.10	1.35	0.23	0.43	1.20***	0.97***	0.61	-2.19*
1F-alpha	1.03***	0.27	1.16***	0.96**	1.10	1.73*	0.32	0.36	1.18***	1.03**	0.70	-1.77
3F-alpha	1.19***	0.23	1.16***	0.81*	0.87	2.40***	0.35	0.49*	1.18***	0.91**	0.14	-1.88
4F-alpha	0.29	0.11	0.67**	0.50	-0.66	0.78	-0.13	0.40	0.74**	0.63**	-0.80	-2.13
Sample: Excluding Microcap Stocks												
Raw	0.83***	0.20	0.97***	0.86*	0.74	1.40	1.16***	0.44	1.24***	0.89**	1.96***	1.30***
1F-alpha	0.90***	0.15	0.94***	0.89**	0.79	1.83*	1.24***	0.38	1.18***	0.94**	2.06**	1.58***
3F-alpha	1.10***	0.04	0.95***	0.71*	0.82	2.51***	1.29***	0.37	1.18***	0.80**	1.80**	1.78***
4F-alpha	0.09	-0.06	0.54*	0.39	-0.86	0.38	0.61***	0.29	0.68**	0.53*	0.55	0.87**

Table A. 3 continued.

	Value-Weight Returns						Equal-Weight Returns					
	Full Period	10 year Sub Periods					Full Period	10 year Sub Periods				
	1965 - 2014	1965 - 1974	1975 - 1984	1985 - 1994	1995 - 2004	2005 - 2014	1965 - 2014	1965 - 1974	1975 - 1984	1985 - 1994	1995 - 2004	2005 - 2014
Panel B: Short-Term Contrarian												
$r_{1,1}$												
Sample: All												
Raw	0.00	-0.15	0.21	0.29	0.08	-0.46	0.75**	0.92***	0.09	0.53	-0.16	2.48*
1F-alpha	-0.18	-0.09	0.15	0.14	-0.31	-0.75	0.60*	1.00***	0.02	0.43	-0.44	2.08*
3F-alpha	-0.07	0.03	0.15	0.24	0.56	-0.82	0.70*	1.12***	0.02	0.56	0.16	2.30
4F-alpha	0.57*	0.14	0.87**	0.33	1.75	0.04	1.09***	1.18***	0.25	0.67**	1.41	2.05
Sample: Excluding Microcap Stocks												
Raw	0.02	0.08	0.25	0.44	-0.61	-0.08	-0.04	0.64**	0.42	0.36	-1.33	-0.29
1F-alpha	-0.13	0.13	0.22	0.33	-0.98	-0.27	-0.17	0.71**	0.38	0.23	-1.64**	-0.41
3F-alpha	-0.10	0.22	0.22	0.36	-0.37	-0.53	-0.06	0.84***	0.38	0.33	-1.09	-0.41
4F-alpha	0.54*	0.33	0.90**	0.42	0.57	0.75	0.45**	0.92***	0.78***	0.47	0.12	-0.09
$r_{1,2}$												
Sample: All												
Raw	-0.24	0.07	0.41	0.23	-1.29	-0.64	0.69**	0.56	0.49	0.18	-0.78	3.16***
1F-alpha	-0.45	0.13	0.28	0.11	-1.84*	-0.89	0.51*	0.64**	0.39	0.05	-1.11	2.70***
3F-alpha	-0.23	0.29	0.28	0.35	-0.87	-0.56	0.67*	0.77**	0.39	0.25	-0.25	3.03***
4F-alpha	0.53*	0.37	0.80**	0.53	0.49	0.69	1.23***	0.82**	0.61**	0.40	1.33	3.21***
Sample: Excluding Microcap Stocks												
Raw	-0.20	0.11	0.19	0.28	-1.27	-0.31	-0.43*	0.39	0.43	0.04	-2.12**	-0.92**
1F-alpha	-0.36	0.17	0.10	0.17	-1.69*	-0.53	-0.59***	0.46*	0.36	-0.10	-2.46***	-1.15***
3F-alpha	-0.18	0.37	0.10	0.40	-0.91	-0.30	-0.43*	0.65**	0.36	0.05	-1.73*	-0.99**
4F-alpha	0.55**	0.47	0.65**	0.56	0.50	0.73	0.23	0.71**	0.73***	0.19	-0.11	-0.38
Panel C: Seasonality												
r^{annual}												
Sample: All												
Raw	0.70***	0.71**	0.37	0.71*	1.33*	0.36	0.29	0.64**	0.24	0.40	0.84**	-0.73
1F-alpha	0.60**	0.70**	0.34	0.61	0.97	0.40	0.24	0.66**	0.21	0.32	0.74*	-0.76
3F-alpha	0.86***	0.67**	0.34	0.83**	1.10	1.02	0.29	0.75***	0.21	0.53*	0.62	-0.98
4F-alpha	0.60**	0.69**	0.13	0.81**	1.06	-0.30	0.31	0.77***	0.28	0.48*	0.70	-0.98
Sample: Excluding Microcap Stocks												
Raw	0.52**	0.82***	0.72**	0.67	0.20	0.16	0.56***	0.42*	0.59**	0.44	0.91***	0.45
1F-alpha	0.44	0.80***	0.67*	0.56	-0.10	0.31	0.53***	0.42*	0.57*	0.38	0.79**	0.51
3F-alpha	0.71***	0.72**	0.67*	0.84**	-0.02	0.94	0.62***	0.41	0.57*	0.64**	0.88**	0.66**
4F-alpha	0.35	0.75**	0.46	0.84**	-0.45	-0.51	0.57***	0.45	0.59*	0.60**	0.80**	0.42
$r^{annual+}$												
Sample: All												
Raw	0.66**	0.49*	0.67	0.54	1.92**	-0.36	-0.11	0.30	0.51*	0.07	0.59	-2.11
1F-alpha	0.60**	0.47**	0.65	0.49	1.69*	-0.41	-0.11	0.28	0.53*	0.00	0.57	-2.04
3F-alpha	0.94***	0.48*	0.66	0.82**	1.50*	0.43	-0.02	0.43**	0.54*	0.29	0.35	-2.13
4F-alpha	0.65**	0.51**	0.42	0.75*	1.05	-0.23	-0.02	0.44**	0.41	0.24	0.31	-1.90
Sample: Excluding Microcap Stocks												
Raw	0.69***	0.52*	0.71*	0.65	0.90	0.69	0.54***	0.42*	0.50	0.10	1.26***	0.42
1F-alpha	0.69***	0.49**	0.75**	0.60	0.83	0.78	0.54***	0.40*	0.58*	0.04	1.21**	0.50
3F-alpha	0.95***	0.42*	0.76**	0.98**	0.72	1.37**	0.68***	0.43**	0.58*	0.39	1.17**	0.63*
4F-alpha	0.59**	0.47*	0.54	0.91**	-0.21	0.86	0.56***	0.45**	0.37	0.33	0.89*	0.54

Table A. 3 continued.

	Value-Weight Returns						Equal-Weight Returns					
	Full Period	10 year Sub Periods					Full Period	10 year Sub Periods				
	1965 - 2014	1965 - 1974	1975 - 1984	1985 - 1994	1995 - 2004	2005 - 2014	1965 - 2014	1965 - 1974	1975 - 1984	1985 - 1994	1995 - 2004	2005 - 2014
Panel D: Long-Term Contrarian												
$r_{25,60}$												
Sample: All												
Raw	-0.29	-0.53	0.07	0.31	-1.42**	0.14	0.46	0.15	0.37	0.41	-0.36	1.80
1F-alpha	-0.24	-0.54*	-0.18	0.37	-1.23**	0.22	0.46	0.15	0.18	0.44	-0.31	1.79
3F-alpha	-0.54**	-0.38	-0.19	-0.11	-1.07**	0.05	0.33	0.15	0.17	0.05	-0.06	1.97
4F-alpha	-0.72***	-0.35	-0.07	-0.23	-1.47**	-0.42	0.16	0.12	0.20	-0.07	-0.38	1.73
Sample: Excluding Microcap Stocks												
Raw	-0.21	-0.33	0.35	0.24	-1.34**	0.01	-0.03	-0.11	0.37	0.41	-0.61	-0.21
1F-alpha	-0.17	-0.33	0.11	0.31	-1.13**	-0.01	-0.03	-0.11	0.13	0.43	-0.53	-0.30
3F-alpha	-0.43**	-0.17	0.09	-0.11	-1.15**	0.06	-0.22	-0.02	0.12	0.03	-0.62*	-0.26
4F-alpha	-0.54**	-0.14	0.20	-0.21	-1.46***	-0.10	-0.31*	-0.02	0.20	-0.10	-0.77**	-0.28
$r_{13,60}$												
Sample: All												
Raw	-0.13	0.03	0.00	0.36	-0.92	-0.10	0.36	0.16	0.26	0.43	-0.55	1.57
1F-alpha	-0.09	0.08	-0.26	0.50	-0.78	-0.01	0.37	0.19	0.06	0.50	-0.52	1.64
3F-alpha	-0.50*	0.21	-0.28	0.02	-0.33	-1.35	0.24	0.17	0.05	0.14	-0.09	1.68
4F-alpha	-0.25	0.23	-0.11	0.03	-0.11	-0.73	0.20	0.18	0.15	0.11	-0.16	1.47
Sample: Excluding Microcap Stocks												
Raw	0.08	0.18	-0.04	0.26	-0.84	0.91	-0.06	0.23	0.02	0.48	-0.64	-0.41
1F-alpha	0.09	0.23	-0.29	0.36	-0.72	0.85	-0.08	0.26	-0.19	0.53	-0.57	-0.57
3F-alpha	-0.25	0.28	-0.31	-0.10	-0.62	0.40	-0.29*	0.24	-0.20	0.12	-0.51	-0.80*
4F-alpha	-0.09	0.29	-0.12	-0.08	-0.46	0.86	-0.24	0.27	-0.09	0.08	-0.43	-0.72*
$r_{13,60}^{ex\ annual}$												
Sample: All												
Raw	-0.07	0.39	0.25	0.77	-1.20*	-0.61	0.54*	0.52**	0.42	0.57	-0.52	1.79
1F-alpha	-0.08	0.44	0.03	0.86*	-1.18*	-0.63	0.52*	0.55**	0.21	0.60	-0.53	1.81
3F-alpha	-0.50*	0.53*	0.01	0.47	-0.89	-1.98*	0.38	0.58**	0.20	0.27	-0.24	1.82
4F-alpha	-0.17	0.57**	0.23	0.47	-0.52	-1.36	0.33	0.60**	0.26	0.27	-0.33	1.55
Sample: Excluding Microcap Stocks												
Raw	0.32	0.41	0.38	0.78*	-0.81	0.85	0.12	0.43*	0.41	0.78**	-0.67	-0.41
1F-alpha	0.30	0.45	0.13	0.87*	-0.75	0.67	0.08	0.47*	0.19	0.81**	-0.64	-0.59
3F-alpha	-0.04	0.54**	0.12	0.41	-0.61	0.20	-0.13	0.50**	0.17	0.43	-0.58	-0.89**
4F-alpha	0.19	0.56**	0.39	0.42	-0.31	0.67	-0.03	0.51**	0.27	0.41	-0.42	-0.68
$r_{13,60}^{ex\ annual+}$												
Sample: All												
Raw	-0.09	0.49	0.24	0.81*	-1.48*	-0.54	0.51	0.64***	0.34	0.68*	-0.06	0.98
1F-alpha	-0.04	0.52	0.08	0.91*	-1.28	-0.49	0.50*	0.66**	0.16	0.72*	-0.03	0.94
3F-alpha	-0.48*	0.48	0.06	0.62	-1.18*	-1.54	0.33	0.63***	0.15	0.49	0.23	0.75
4F-alpha	-0.36	0.50	0.19	0.58	-1.15*	-1.35	0.26	0.64***	0.19	0.46	0.11	0.33
Sample: Excluding Microcap Stocks												
Raw	0.28	0.57*	0.35	0.73*	-0.99	0.74	0.20	0.58**	0.37	0.71*	-0.42	-0.24
1F-alpha	0.32	0.60*	0.21	0.82	-0.79	0.69	0.19	0.61**	0.19	0.75*	-0.35	-0.39
3F-alpha	-0.05	0.57**	0.20	0.54	-0.87*	0.47	-0.03	0.54**	0.18	0.46	-0.29	-0.67*
4F-alpha	0.01	0.59**	0.41	0.50	-0.90*	0.57	0.01	0.56**	0.26	0.41	-0.33	-0.54

Table A. 4: Returns on Various Strategies, Rebalancing Every Six Month

At the beginning of each sixth month $t = 1{:}\,01/1965$ to $t = 594 = T{:}\,06/2014$ stocks are ranked according to the compounded total return over specific contiguous and non-contiguous lags (see Table 3 for details). Decile portfolios are formed based on this ranking and returns are equal-weight or by the stock's market capitalization (value-weight) at the beginning of month t. In value-weight portfolios the maximum weight is limited to 50%. Thus, decile portfolios are rebalanced every six months. A given momentum or seasonality (contrarian) strategy is short (long) in decile one and long (short) in decile ten.
Presented are average monthly raw returns and alphas obtained from one factor (Jensen (1968)), three factor (Fama/French (1993)) and four factor (Carhart (1997)) regressions. Shown are results for a sample of all stocks of all sizes and in addition for a sub-sample that excludes microcap stocks (<€50 mio, recursively adjusted by inflation, see Section 3 for details). Test statistics for alphas are based on Newey-West standard errors. Asterisks ***, **, * signal a significance level of 1%, 5%, and 10%.

	Value-Weight Returns						Equal-Weight Returns					
	Full Period	10 year Sub Periods					Full Period	10 year Sub Periods				
	1965 - 2014	1965 - 1974	1975 - 1984	1985 - 1994	1995 - 2004	2005 - 2014	1965 - 2014	1965 - 1974	1975 - 1984	1985 - 1994	1995 - 2004	2005 - 2014
Panel A: Momentum												
$r_{2,12}$												
Sample: All												
Raw	0.88**	0.37	1.13**	0.93*	0.24	1.77	0.31	0.31	0.92**	0.88**	1.77*	-2.48*
1F-alpha	1.01***	0.34	1.13***	0.93*	0.47	2.48**	0.45	0.25	0.92***	0.96**	2.01**	-2.02*
3F-alpha	1.08***	0.28	1.13***	0.83*	-0.26	3.12***	0.34	0.33	0.92***	0.84**	1.04	-2.20*
4F-alpha	-0.21	0.14	0.30	0.40	-2.41**	0.72	-0.38	0.20	0.26	0.48	-0.38	-2.70**
Sample: Excluding Microcap Stocks												
Raw	0.95***	0.40	1.17***	1.15**	0.40	1.64	1.39***	0.25	0.94***	0.96**	2.98***	1.85***
1F-alpha	1.06***	0.36	1.16***	1.17**	0.55	2.24**	1.52***	0.19	0.92***	1.03**	3.25***	2.16***
3F-alpha	1.12***	0.28	1.16***	1.04**	0.02	2.83***	1.40***	0.11	0.92***	0.88**	2.53***	2.30***
4F-alpha	-0.11	0.14	0.44	0.58	-2.11**	0.59	0.51***	-0.03	0.21	0.50*	1.03*	1.07***
$r_{3,12}$												
Sample: All												
Raw	0.75**	0.25	0.86**	0.83	0.44	1.39	0.30	0.44	0.87**	0.82**	1.41	-2.15**
1F-alpha	0.88**	0.22	0.82**	0.87*	0.66	2.03*	0.43	0.38	0.86**	0.90**	1.61*	-1.69*
3F-alpha	0.92***	0.16	0.82**	0.73	-0.23	2.79***	0.33	0.48	0.85**	0.75*	0.70	-1.79*
4F-alpha	-0.29	0.03	0.12	0.33	-2.27**	0.62	-0.34	0.36	0.19	0.38	-0.62	-2.16**
Sample: Excluding Microcap Stocks												
Raw	0.86***	0.08	0.83**	0.92*	0.85	1.65	1.08***	0.14	0.58*	0.79**	2.25***	1.69***
1F-alpha	0.97***	0.03	0.80**	0.93*	1.05	2.17*	1.20***	0.08	0.56*	0.87**	2.49***	2.00***
3F-alpha	1.06***	-0.04	0.80**	0.79	0.61	2.86***	1.10***	0.01	0.56**	0.68	1.86**	2.17***
4F-alpha	-0.10	-0.19	0.10	0.39	-1.21	0.64	0.24	-0.13	-0.13	0.31	0.48	0.88**
$r_{7,12}$												
Sample: All												
Raw	0.62**	-0.01	1.03***	0.49	1.17	0.40	0.01	0.26	0.91***	0.56	0.77	-2.59**
1F-alpha	0.63**	-0.06	0.97***	0.47	1.12	0.61	0.10	0.20	0.89***	0.57	0.88	-2.18*
3F-alpha	0.78***	-0.14	0.97***	0.35	0.22	1.44*	0.07	0.34	0.89***	0.51	0.23	-2.34*
4F-alpha	0.05	-0.21	0.45	0.07	-0.70	0.03	-0.36	0.27	0.48	0.28	-0.64	-2.59**
Sample: Excluding Microcap Stocks												
Raw	0.62**	-0.15	0.71**	0.52	1.52*	0.47	0.91***	0.24	0.84***	0.39	1.79***	1.29***
1F-alpha	0.65**	-0.18	0.66**	0.51	1.55	0.73	0.96***	0.20	0.80***	0.38	1.94***	1.47***
3F-alpha	0.83***	-0.26	0.66**	0.39	1.24	1.49**	0.96***	0.23	0.80***	0.29	1.56**	1.74***
4F-alpha	0.03	-0.32	0.27	0.10	0.08	-0.20	0.36**	0.17	0.37	0.10	0.45	0.84**

Table A. 4 continued.

	Value-Weight Returns						Equal-Weight Returns					
	Full Period	10 year Sub Periods					Full Period	10 year Sub Periods				
	1965 - 2014	1965 - 1974	1975 - 1984	1985 - 1994	1995 - 2004	2005 - 2014	1965 - 2014	1965 - 1974	1975 - 1984	1985 - 1994	1995 - 2004	2005 - 2014
Panel B: Short-Term Contrarian												
$r_{1,1}$												
Sample: All												
Raw	-0.11	0.12	-0.15	0.48	0.02	-1.05	0.18	0.38	-0.29	0.00	-0.64	1.49
1F-alpha	-0.19	0.16	-0.17	0.55	-0.27	-1.18*	0.11	0.46	-0.33	0.03	-0.87	1.53
3F-alpha	-0.14	0.18	-0.16	0.50	0.50	-1.27*	0.07	0.41	-0.33	-0.07	-0.05	0.96
4F-alpha	0.43	0.27	0.39	0.69	1.71	-1.00	0.48	0.45	-0.03	0.10	1.01	0.81
Sample: Excluding Microcap Stocks												
Raw	0.13	0.32	0.02	0.58	-0.51	0.25	-0.35	0.42	-0.17	0.15	-1.72**	-0.44
1F-alpha	0.06	0.36	0.00	0.65	-0.83	0.28	-0.44**	0.49*	-0.19	0.14	-1.99***	-0.52
3F-alpha	0.03	0.31	0.01	0.59	-0.29	-0.30	-0.39*	0.46	-0.19	0.07	-1.24	-0.66
4F-alpha	0.55**	0.41	0.50	0.76	1.03	-0.48	0.15	0.53*	0.23	0.27	0.04	-0.43
$r_{1,2}$												
Sample: All												
Raw	-0.62**	-0.10	-0.52	0.05	-1.10	-1.48*	0.18	0.08	-0.30	-0.28	-0.98	2.50**
1F-alpha	-0.75***	-0.02	-0.61*	0.06	-1.56**	-1.45*	0.04	0.18	-0.33	-0.31	-1.26	2.20**
3F-alpha	-0.59**	-0.02	-0.61*	0.22	-0.57	-1.29	0.14	0.22	-0.34	-0.37	-0.29	2.53**
4F-alpha	-0.10	0.10	0.00	0.49	0.38	-1.49	0.60*	0.32	-0.02	-0.18	0.78	2.60**
Sample: Excluding Microcap Stocks												
Raw	-0.45*	0.02	-0.59*	0.02	-1.03	-0.69	-0.84***	0.11	-0.33	-0.28	-2.30**	-1.45***
1F-alpha	-0.55**	0.09	-0.65**	0.03	-1.33	-0.73	-0.96***	0.20	-0.37	-0.31	-2.58***	-1.63***
3F-alpha	-0.40	0.13	-0.65*	0.22	-0.28	-0.69	-0.86***	0.27	-0.37	-0.32	-1.61*	-1.68***
4F-alpha	0.11	0.24	-0.09	0.48	0.79	-0.80	-0.24	0.37	0.08	-0.10	-0.40	-1.16***
Panel C: Seasonality												
r^{annual}												
Sample: All												
Raw	0.68***	0.55	0.69**	0.79**	1.38*	-0.05	0.15	0.03	0.33	0.62**	0.76*	-1.02
1F-alpha	0.58**	0.58	0.61*	0.82**	1.02	-0.16	0.10	0.08	0.25	0.62**	0.63	-1.02
3F-alpha	0.86***	0.64	0.61*	0.99***	1.22*	0.40	0.19	0.22	0.26	0.77***	0.55	-0.99
4F-alpha	0.82***	0.66	0.59*	0.92**	1.43**	-0.02	0.23	0.27	0.23	0.71***	0.70	-0.91
Sample: Excluding Microcap Stocks												
Raw	0.61**	0.54*	0.87**	0.70*	0.83	0.07	0.44***	0.00	0.64**	0.60**	0.84**	0.10
1F-alpha	0.54*	0.56*	0.78**	0.74*	0.47	0.31	0.38***	0.05	0.56**	0.59**	0.66*	0.16
3F-alpha	0.86***	0.54	0.78**	0.90**	0.65	0.98	0.48***	-0.01	0.56**	0.74***	0.80**	0.28
4F-alpha	0.54**	0.54	0.80**	0.83**	0.48	-0.50	0.45***	0.02	0.57**	0.67**	0.89***	-0.03
$r^{annual+}$												
Sample: All												
Raw	0.48*	-0.34	1.06***	0.23	0.55	0.90	-0.29	-0.42*	0.42	-0.04	0.76*	-2.26
1F-alpha	0.43	-0.35	1.06***	0.17	0.39	0.92	-0.29	-0.41*	0.42	-0.16	0.73	-1.95
3F-alpha	0.78***	-0.44	1.07***	0.39	0.37	1.66*	-0.25	-0.30	0.42	0.00	0.62	-2.41*
4F-alpha	0.34	-0.44	0.92***	0.30	-0.36	0.64	-0.25	-0.29	0.30	-0.02	0.67	-2.27**
Sample: Excluding Microcap Stocks												
Raw	0.21	-0.15	0.76**	0.08	0.37	-0.04	0.05	-0.28	0.39	-0.33	0.51	-0.03
1F-alpha	0.18	-0.16	0.80***	0.01	0.23	0.06	0.01	-0.27	0.44	-0.47	0.45	0.00
3F-alpha	0.50**	-0.32	0.81***	0.30	0.35	0.53	0.16	-0.29	0.44	-0.16	0.58	0.12
4F-alpha	0.15	-0.29	0.75***	0.25	-0.34	-0.36	0.13	-0.28	0.28	-0.16	0.56	0.09

Table A. 4 continued.

	Value-Weight Returns						Equal-Weight Returns					
	Full Period	10 year Sub Periods					Full Period	10 year Sub Periods				
	1965 - 2014	1965 - 1974	1975 - 1984	1985 - 1994	1995 - 2004	2005 - 2014	1965 - 2014	1965 - 1974	1975 - 1984	1985 - 1994	1995 - 2004	2005 - 2014
Panel D: Long-Term Contrarian												
$r_{25,60}$												
Sample: All												
Raw	-0.12	-0.41	0.12	0.68	-1.16**	0.20	0.49*	0.15	0.20	0.68*	-0.38	1.85
1F-alpha	-0.06	-0.43	-0.10	0.72	-1.00*	0.45	0.49*	0.14	0.02	0.70	-0.34	1.90
3F-alpha	-0.32	-0.29	-0.11	0.21	-0.93*	0.32	0.38	0.20	0.01	0.28	-0.12	2.12
4F-alpha	-0.45*	-0.25	0.01	0.11	-1.26**	0.05	0.21	0.18	0.04	0.11	-0.38	1.90
Sample: Excluding Microcap Stocks												
Raw	-0.03	-0.14	0.37	0.53	-1.31**	0.44	0.00	-0.07	0.34	0.65*	-0.82**	-0.09
1F-alpha	0.01	-0.16	0.16	0.59	-1.13**	0.44	0.00	-0.07	0.11	0.67	-0.75**	-0.12
3F-alpha	-0.23	0.00	0.15	0.12	-1.34***	0.64	-0.19	0.03	0.10	0.21	-0.91***	-0.05
4F-alpha	-0.25	0.05	0.25	0.03	-1.48***	0.80	-0.29*	0.04	0.16	0.05	-1.04***	-0.09
$r_{13,60}$												
Sample: All												
Raw	-0.02	-0.22	0.21	0.66	-0.82	0.05	0.40	0.27	0.21	0.44	-0.55	1.69
1F-alpha	0.02	-0.18	-0.01	0.76	-0.66	0.20	0.42	0.29	0.03	0.51	-0.50	1.79
3F-alpha	-0.43*	-0.08	-0.03	0.26	-0.34	-1.35	0.26	0.16	0.02	0.13	-0.08	1.78
4F-alpha	-0.31	-0.06	0.14	0.21	-0.34	-1.13	0.16	0.14	0.08	0.08	-0.23	1.43
Sample: Excluding Microcap Stocks												
Raw	0.12	0.11	-0.09	0.68	-0.57	0.51	-0.09	0.21	-0.01	0.57	-0.71*	-0.51
1F-alpha	0.14	0.15	-0.34	0.74	-0.43	0.59	-0.09	0.24	-0.24	0.61	-0.62	-0.61
3F-alpha	-0.25	0.21	-0.35	0.25	-0.41	-0.10	-0.33*	0.23	-0.25	0.20	-0.61	-0.85
4F-alpha	-0.12	0.23	-0.17	0.20	-0.10	0.06	-0.33**	0.25	-0.19	0.11	-0.63	-0.74
$r_{13,60}^{ex\ annual}$												
Sample: All												
Raw	0.22	0.19	0.15	0.73	-0.78	0.88	0.50	0.36	0.28	0.61	-0.23	1.55
1F-alpha	0.21	0.25	-0.07	0.83	-0.82	0.92	0.49	0.40	0.06	0.69	-0.25	1.61
3F-alpha	-0.19	0.32	-0.09	0.37	-0.52	-0.44	0.35	0.40	0.05	0.30	0.06	1.65
4F-alpha	0.05	0.34	0.15	0.32	-0.06	-0.22	0.26	0.40	0.06	0.25	-0.03	1.29
Sample: Excluding Microcap Stocks												
Raw	0.32	0.27	0.42	0.69	-0.57	0.83	-0.04	0.18	0.31	0.72*	-0.85**	-0.56
1F-alpha	0.31	0.33	0.17	0.80	-0.53	0.78	-0.06	0.23	0.09	0.78*	-0.83*	-0.65
3F-alpha	-0.03	0.40*	0.15	0.34	-0.32	0.16	-0.27	0.28	0.07	0.38	-0.76*	-0.88
4F-alpha	0.17	0.43*	0.37	0.29	0.14	0.40	-0.21	0.30	0.13	0.31	-0.62	-0.75
$r_{13,60}^{ex\ annual+}$												
Sample: All												
Raw	-0.16	-0.08	-0.11	0.49	-1.16*	0.07	0.50	0.39	0.34	0.35	0.06	1.38
1F-alpha	-0.14	-0.01	-0.27	0.51	-1.04	0.23	0.48	0.42	0.14	0.37	0.09	1.43
3F-alpha	-0.52**	-0.10	-0.28	0.19	-0.86*	-0.89	0.34	0.35	0.13	0.10	0.35	1.49
4F-alpha	-0.46*	-0.06	-0.13	0.14	-0.92*	-0.85	0.24	0.36	0.12	0.05	0.24	1.12
Sample: Excluding Microcap Stocks												
Raw	0.13	0.12	0.01	0.57	-0.62	0.59	-0.03	0.13	0.23	0.48	-0.59	-0.43
1F-alpha	0.13	0.19	-0.14	0.60	-0.50	0.54	-0.06	0.19	0.00	0.48	-0.52	-0.52
3F-alpha	-0.20	0.11	-0.15	0.23	-0.45	0.26	-0.26*	0.15	-0.01	0.18	-0.46	-0.79*
4F-alpha	-0.18	0.14	0.01	0.14	-0.54	0.38	-0.26	0.17	0.03	0.10	-0.48	-0.70

Table A. 5: Returns on Various Strategies, Rebalancing Every Twelve Month

At the beginning of each twelfth month $t = 1{:}\,01/1965$ to $t = 594 = T{:}\,06/2014$ stocks are ranked according to the compounded total return over specific contiguous and non-contiguous lags (see Table 3 for details). Decile portfolios are formed based on this ranking and returns are equal-weight or by the stock's market capitalization (value-weight) at the beginning of month t. In value-weight portfolios the maximum weight is limited to 50%. Thus, decile portfolios are rebalanced every twelve months. A given momentum or seasonality (contrarian) strategy is short (long) in decile one and long (short) in decile ten.
Presented are average monthly raw returns and alphas obtained from one factor (Jensen (1968)), three factor (Fama/French (1993)) and four factor (Carhart (1997)) regressions. Shown are results for a sample of all stocks of all sizes and in addition for a sub-sample that excludes microcap stocks (<€50 mio, recursively adjusted by inflation, see Section 3 for details). Test statistics for alphas are based on Newey-West standard errors. Asterisks ***, **, * signal a significance level of 1%, 5%, and 10%.

	Value-Weight Returns						Equal-Weight Returns					
	Full Period	10 year Sub Periods					Full Period	10 year Sub Periods				
	1965 - 2014	1965 - 1974	1975 - 1984	1985 - 1994	1995 - 2004	2005 - 2014	1965 - 2014	1965 - 1974	1975 - 1984	1985 - 1994	1995 - 2004	2005 - 2014
Panel A: Momentum												
$r_{2,12}$												
Sample: All												
Raw	0.44	-0.15	0.92**	0.39	0.06	1.06	-0.13	0.23	0.67*	0.38	0.78	-3.02**
1F-alpha	0.57*	-0.20	0.96**	0.46	0.24	1.59	0.00	0.17	0.68**	0.43	1.01	-2.59**
3F-alpha	0.60*	-0.32	0.96***	0.33	-0.33	1.92**	-0.11	0.17	0.68**	0.33	0.17	-2.78**
4F-alpha	-0.49	-0.40	0.20	-0.04	-2.40**	0.15	-0.68**	0.08	0.12	0.00	-1.12	-2.86**
Sample: Excluding Microcap Stocks												
Raw	0.47	-0.32	1.09***	0.52	0.23	0.88	0.78***	-0.09	0.91***	0.29	1.81**	1.03*
1F-alpha	0.56*	-0.37	1.09***	0.56	0.32	1.38	0.90***	-0.15	0.87***	0.33	2.10***	1.31**
3F-alpha	0.66**	-0.55*	1.08***	0.46	-0.04	1.87**	0.79***	-0.22	0.87***	0.24	1.48*	1.50***
4F-alpha	-0.41	-0.65**	0.44	0.07	-1.91**	-0.09	0.01	-0.30	0.26	-0.09	-0.05	0.64
$r_{3,12}$												
Sample: All												
Raw	0.26	-0.44	0.88**	0.34	-0.21	0.80	-0.17	0.20	0.55	0.39	0.35	-2.55**
1F-alpha	0.37	-0.50	0.85**	0.39	-0.07	1.32	-0.04	0.12	0.58*	0.42	0.55	-2.07**
3F-alpha	0.44	-0.42	0.85**	0.27	-0.44	1.75**	-0.13	0.11	0.57*	0.32	-0.09	-2.15**
4F-alpha	-0.50	-0.47	0.17	-0.05	-2.28**	0.27	-0.64**	0.02	-0.01	0.02	-1.22	-2.13**
Sample: Excluding Microcap Stocks												
Raw	0.24	-0.65*	0.99***	0.26	-0.29	0.94	0.52**	-0.19	0.62*	0.27	0.90	1.03*
1F-alpha	0.31	-0.70**	0.95***	0.29	-0.21	1.32	0.62***	-0.26	0.60*	0.29	1.16	1.29**
3F-alpha	0.42	-0.63*	0.95***	0.23	-0.44	1.82**	0.51**	-0.27	0.60*	0.19	0.66	1.49***
4F-alpha	-0.50*	-0.70**	0.35	-0.07	-2.00**	-0.05	-0.20	-0.34**	0.00	-0.14	-0.63	0.51
$r_{7,12}$												
Sample: All												
Raw	0.12	-0.52	0.91***	-0.02	-0.59	0.90	-0.38	-0.15	0.37	0.15	-0.33	-2.12**
1F-alpha	0.12	-0.55	0.83**	0.04	-0.67	0.99	-0.32	-0.21	0.36	0.18	-0.26	-1.91*
3F-alpha	0.31	-0.58	0.83***	-0.25	-0.88	1.77*	-0.37	-0.26	0.36	-0.01	-0.63	-2.13*
4F-alpha	-0.23	-0.64*	0.37	-0.44	-1.86**	1.08	-0.72***	-0.30	0.06	-0.19	-1.47*	-2.28*
Sample: Excluding Microcap Stocks												
Raw	-0.03	-0.44	0.66**	-0.02	0.05	-0.45	0.38*	-0.07	0.45	0.16	0.45	0.94**
1F-alpha	-0.01	-0.46	0.58*	0.02	0.03	-0.28	0.42**	-0.11	0.38	0.17	0.56	1.10**
3F-alpha	0.13	-0.49	0.58**	-0.24	-0.02	0.27	0.39**	-0.18	0.37	-0.03	0.34	1.37***
4F-alpha	-0.55**	-0.54*	0.28	-0.43	-1.59*	-0.61	-0.13	-0.22	0.12	-0.21	-0.92	0.90**

Table A. 5 continued.

	Value-Weight Returns						Equal-Weight Returns					
	Full Period	10 year Sub Periods					Full Period	10 year Sub Periods				
	1965 - 2014	1965 - 1974	1975 - 1984	1985 - 1994	1995 - 2004	2005 - 2014	1965 - 2014	1965 - 1974	1975 - 1984	1985 - 1994	1995 - 2004	2005 - 2014
Panel B: Short-Term Contrarian												
$r_{1,1}$												
Sample: All												
Raw	0.03	-0.23	0.22	0.93**	0.45	-1.35*	0.22	0.18	0.11	-0.06	0.05	0.89
1F-alpha	-0.01	-0.17	0.14	0.93**	0.44	-1.50**	0.17	0.27	0.04	-0.09	-0.04	0.98
3F-alpha	-0.18	-0.13	0.14	1.02**	0.57	-1.64**	0.04	0.17	0.04	-0.06	0.41	0.37
4F-alpha	0.27	-0.07	0.65	1.14**	1.25	-0.81	0.38	0.20	0.30	0.13	1.42	0.06
Sample: Excluding Microcap Stocks												
Raw	0.11	0.07	0.33	1.11***	-0.39	-0.64	-0.21	0.14	-0.08	0.19	-0.85	-0.49
1F-alpha	0.08	0.12	0.26	1.09***	-0.43	-0.60	-0.26	0.22	-0.16	0.14	-0.92	-0.44
3F-alpha	-0.02	0.15	0.26	1.15***	-0.46	-0.24	-0.32	0.20	-0.16	0.22	-0.63	-0.48
4F-alpha	0.22	0.21	0.67*	1.26***	0.45	-0.73	0.10	0.24	0.24	0.41	0.55	-0.40
$r_{1,2}$												
Sample: All												
Raw	-0.38	-0.22	-0.37	0.38	-0.05	-1.77*	0.15	-0.33	-0.25	-0.19	0.01	1.68
1F-alpha	-0.41	-0.13	-0.43	0.32	0.00	-1.78*	0.08	-0.25	-0.23	-0.26	-0.09	1.50
3F-alpha	-0.35	0.18	-0.43	0.50	1.04	-1.17	0.04	-0.20	-0.23	-0.20	0.63	1.40
4F-alpha	-0.10	0.29	0.09	0.72	1.40	-1.49	0.43	-0.12	-0.02	0.05	1.63*	1.25
Sample: Excluding Microcap Stocks												
Raw	-0.22	0.07	-0.41	0.25	-0.11	-0.99	-0.58***	-0.16	-0.42	-0.21	-1.10	-1.04***
1F-alpha	-0.24	0.15	-0.44	0.21	-0.06	-1.03	-0.64***	-0.09	-0.46*	-0.28	-1.14	-1.19***
3F-alpha	-0.24	0.41	-0.44	0.39	0.57	-0.60	-0.70***	0.06	-0.46*	-0.19	-0.71	-1.23***
4F-alpha	0.04	0.50*	0.04	0.61	1.02	-0.73	-0.20	0.13	-0.09	0.07	0.37	-0.94**
Panel C: Seasonality												
r^{annual}												
Sample: All												
Raw	0.41*	-0.19	0.67*	0.01	1.18*	0.37	-0.21	-0.13	0.40	0.13	-0.16	-1.43
1F-alpha	0.31	-0.15	0.51	0.00	0.85	0.42	-0.24	-0.08	0.33	0.18	-0.34	-1.21
3F-alpha	0.48**	-0.08	0.51	0.05	1.08*	0.43	-0.22	0.01	0.33	0.17	-0.14	-1.53
4F-alpha	0.41*	-0.09	0.39	0.05	0.84	0.39	-0.09	0.03	0.32	0.16	-0.02	-1.15
Sample: Excluding Microcap Stocks												
Raw	0.34	-0.33	0.77**	-0.04	1.46**	-0.22	0.08	-0.08	0.63**	0.26	-0.12	-0.36
1F-alpha	0.25	-0.29	0.60*	-0.06	1.14*	-0.08	0.01	-0.03	0.50*	0.27	-0.33	-0.29
3F-alpha	0.42*	-0.21	0.60*	-0.02	1.27**	0.03	0.03	-0.03	0.50*	0.20	-0.11	-0.26
4F-alpha	0.37	-0.24	0.54	-0.02	1.10*	0.15	0.07	-0.02	0.54*	0.19	-0.10	-0.20
$r^{annual+}$												
Sample: All												
Raw	0.32	0.14	0.78**	0.08	1.10	-0.59	-0.20	-0.20	0.21	-0.07	0.07	-1.11
1F-alpha	0.27	0.10	0.72**	0.07	0.92	-0.67	-0.24	-0.19	0.18	-0.07	-0.05	-1.13
3F-alpha	0.41	-0.11	0.72**	-0.01	0.81	-0.63	-0.20	-0.13	0.18	-0.15	-0.05	-1.30
4F-alpha	0.39	-0.08	0.60**	-0.02	0.44	-0.09	-0.16	-0.11	0.04	-0.12	0.02	-1.18
Sample: Excluding Microcap Stocks												
Raw	0.29	0.36	0.68**	-0.02	0.70	-0.31	0.08	0.25	0.38	-0.10	0.11	-0.27
1F-alpha	0.25	0.34	0.63**	-0.03	0.52	-0.34	0.04	0.25	0.37	-0.10	-0.06	-0.30
3F-alpha	0.39	0.12	0.63**	-0.09	0.43	-0.28	0.09	0.18	0.37	-0.18	0.07	-0.23
4F-alpha	0.37	0.15	0.52*	-0.11	0.12	0.16	0.12	0.19	0.19	-0.16	0.06	-0.11

Table A. 5 continued.

	Value-Weight Returns						Equal-Weight Returns					
	Full Period	10 year Sub Periods					Full Period	10 year Sub Periods				
	1965 - 2014	1965 - 1974	1975 - 1984	1985 - 1994	1995 - 2004	2005 - 2014	1965 - 2014	1965 - 1974	1975 - 1984	1985 - 1994	1995 - 2004	2005 - 2014
Panel D: Long-Term Contrarian												
$r_{25,60}$												
Sample: All												
Raw	-0.29	-0.25	0.28	0.58	-1.92***	-0.15	0.37	0.15	0.11	0.25	-0.52	2.04
1F-alpha	-0.25	-0.26	0.04	0.58	-1.73***	-0.07	0.37	0.14	-0.07	0.24	-0.47	2.10*
3F-alpha	-0.50**	-0.22	0.03	0.10	-1.56***	-0.19	0.27	0.13	-0.08	-0.07	-0.30	2.36*
4F-alpha	-0.66***	-0.19	0.06	-0.01	-2.06***	-0.35	0.10	0.13	-0.08	-0.19	-0.52	2.03
Sample: Excluding Microcap Stocks												
Raw	-0.17	-0.08	0.33	0.39	-1.67***	0.21	-0.16	0.06	0.17	0.27	-1.22***	-0.09
1F-alpha	-0.15	-0.07	0.11	0.43	-1.52***	0.21	-0.17	0.07	-0.06	0.26	-1.12***	-0.16
3F-alpha	-0.35*	0.07	0.10	-0.01	-1.50***	0.33	-0.33**	0.16	-0.07	-0.06	-1.19***	-0.14
4F-alpha	-0.37*	0.10	0.12	-0.10	-1.60***	0.50	-0.43***	0.18	-0.09	-0.21	-1.36***	-0.13
$r_{13,60}$												
Sample: All												
Raw	-0.02	-0.23	0.23	0.71	-0.87	0.07	0.46	0.20	0.13	0.53	-0.72	2.32
1F-alpha	0.04	-0.20	-0.05	0.80*	-0.64	0.25	0.46	0.21	-0.08	0.60	-0.67	2.36
3F-alpha	-0.42	-0.17	-0.06	0.26	-0.36	-1.23	0.30	0.05	-0.09	0.20	-0.35	2.35
4F-alpha	-0.44	-0.14	0.05	0.20	-0.78	-1.09	0.17	0.05	-0.05	0.14	-0.48	1.85
Sample: Excluding Microcap Stocks												
Raw	-0.13	0.04	0.03	0.69	-0.61	-0.87	-0.20	0.22	0.05	0.72*	-1.20***	-0.85**
1F-alpha	-0.10	0.07	-0.26	0.78*	-0.45	-0.88	-0.22	0.25	-0.21	0.76*	-1.14**	-0.99**
3F-alpha	-0.46**	0.04	-0.27	0.23	-0.44	-1.18*	-0.43**	0.17	-0.22	0.32	-1.11***	-1.13**
4F-alpha	-0.41**	0.06	-0.09	0.14	-0.47	-0.87	-0.45***	0.18	-0.14	0.22	-1.19***	-0.98**
$r_{13,60}^{ex\ annual}$												
Sample: All												
Raw	0.00	0.09	-0.20	0.75	-1.17	0.60	0.38	0.22	0.28	0.43	-0.73	1.87
1F-alpha	0.03	0.14	-0.48	0.85*	-0.97	0.56	0.37	0.27	0.03	0.49	-0.71	1.91
3F-alpha	-0.34	0.15	-0.50	0.32	-0.77	-0.15	0.23	0.19	0.02	0.09	-0.39	2.04
4F-alpha	-0.32	0.15	-0.28	0.26	-0.86	-0.08	0.12	0.18	0.07	0.06	-0.56	1.69
Sample: Excluding Microcap Stocks												
Raw	-0.12	0.08	-0.07	0.66	-0.54	-0.80	-0.26	0.18	0.07	0.60	-1.25***	-0.97***
1F-alpha	-0.10	0.14	-0.34	0.77	-0.39	-0.83	-0.28	0.23	-0.19	0.64	-1.20**	-1.05**
3F-alpha	-0.42**	0.15	-0.36	0.21	-0.25	-1.00*	-0.51***	0.23	-0.20	0.19	-1.13***	-1.26***
4F-alpha	-0.32*	0.16	-0.19	0.16	-0.14	-0.60	-0.50***	0.22	-0.16	0.13	-1.19***	-1.11***
$r_{13,60}^{ex\ annual+}$												
Sample: All												
Raw	-0.28	0.09	-0.48	0.45	-0.88	-0.61	0.46	0.37	0.23	0.19	-0.43	2.11
1F-alpha	-0.27	0.12	-0.72*	0.49	-0.77	-0.54	0.44	0.40*	0.00	0.24	-0.42	2.09
3F-alpha	-0.65***	0.00	-0.73**	0.00	-0.66	-1.18	0.30	0.30	-0.01	-0.14	-0.15	2.22
4F-alpha	-0.58***	0.02	-0.62*	-0.02	-0.64	-1.08	0.19	0.29	-0.03	-0.15	-0.21	1.72
Sample: Excluding Microcap Stocks												
Raw	0.09	0.26	-0.34	0.42	-0.38	0.54	-0.10	0.36	0.05	0.37	-0.94**	-0.39
1F-alpha	0.10	0.30	-0.60	0.49	-0.21	0.40	-0.14	0.41*	-0.21	0.38	-0.91**	-0.52
3F-alpha	-0.31	0.25	-0.62**	-0.02	-0.21	-0.27	-0.37**	0.36	-0.22	-0.04	-0.87**	-0.85**
4F-alpha	-0.15	0.28	-0.46	-0.03	-0.16	0.37	-0.35**	0.37	-0.15	-0.09	-0.87**	-0.78*

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V. Do Insiders and Their Imitators Trade Profitably? Index-Specific Evidence from Germany

Do Insiders and Their Imitators Trade Profitably? Index-Specific Evidence from Germany*

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Abstract

For the U.S it has been shown that insiders and their imitators, on average, do not earn profits net of transaction costs. For Germany, we find that profitable insider trading is related to index membership. For the TecDAX, we find for purchases that insiders and imitators earn large and statistically significant abnormal returns net of transaction costs. Conversely, abnormal returns for purchases by insiders of stocks included in the DAX are indistinguishable from zero. The results survive a number of robustness checks and are examined under various methodological variations. These variations have implications for the inference drawn from the data and are relevant for event studies in general.

Keywords: directors' dealings, event study, transaction costs, bid-ask spread, DAX, TecDAX

JEL Classification: G14

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1. Introduction

In the regulation of insider transactions, like in the regulation of other aspects of security markets, Germany has been a bit behind the U.S. and the U.K. Insider transactions based on private, non-public information were made a crime by German legislation only in 1994.[1] Insiders have only been required to publish their transactions since 2002 - 68 years after the U.S. As a result, research on German insider transactions also began later than in the U.S. Existing German studies typically use the standard short-term event study methodology and find statistically significant average cumulative abnormal returns (CARs) from the purchase day to day +20 of more than 2%.

A (mean) CAR of about 2% was also found in many U.S. studies in the early eighties. This indicates that market participants think that insiders, on average, have an informational advantage. But do they profit from it? Seyhun (1986) argues that insider trades and their imitation by outside investors are associated with transaction costs, especially bid-ask spreads, which in the case of small firms may be high. He concludes for the U.S. that when transaction costs are taken into account, insiders' abnormal returns are much lower than those reported in earlier studies, and that the abnormal return on imitation strategies, on average, is negative. Lin/Howe (1990) find for the OTC/NASDAQ market that the large bid-ask spreads eliminate the returns for insider trades. Friederich/Gregory/Matatko/Tonks (2002) arrive at the same conclusion for British mid-cap companies.

Transaction costs are typically not considered in existing German studies, Stotz (2006) and Dickgiesser/Kaserer (2010) are notable exceptions. Stotz (2006) assumes and employs a transaction cost of 1% for the German market, and concludes that, "insiders who buy can still reap profits of 1.73% after 25 days". His estimate for imitators, that is non-insiders that buy on the publication day, is similar (1.81%). Dickgiesser/Kaserer (2010) take bid-ask spreads in a more realistic way into account and find, on the other hand, that imitators of insider transactions cannot make arbitrage profits. So the magnitude of the transaction costs, notably the bid-ask spreads, plays a key role in answering the question whether insiders and their imitators, on average, profit from their transactions in Germany.

Consistent with existing studies we find that stocks included in the DAX have very low bid-ask spreads; in our sample the mean is 0.15%. The spreads are slightly higher for MDAX, SDAX, and TecDAX stocks and really high for German stocks not included in one of these indices, which we call "OTHERS". More than 50% of the insider trades in our sample occur in the OTHERS category. For these firms, the bid-ask spread is typically more than 2% and therefore reduces (abnormal) returns significantly. Based on this finding we ask: Do insiders of the stocks included in one of the four mentioned indices, because of their low bid-ask spreads, on average, profit from their transactions? Can the insiders of firms not included in

[1] Since 1970 voluntary insider trading guidelines had existed. Standen (1995) summarizes the situation before 1994 and the legislation introduced in that year. He observes that, "there is little sign of any real desire on the part of the 'insiders' to change this rather cozy arrangement".

one of the indices achieve profits because of the higher information asymmetry, even though their bid-ask spreads are much higher?

Based on the data from the Federal Financial Supervisory Authority (Bundesanstalt für Finanzdienstleistungsaufsicht, BaFin) and Insiderdaten.de, our major results for purchases are as follows:[2]

- The average CAR for our full sample of 7,630 purchases is 2.69% when transaction costs are excluded (gross CAR) and 1.06% after deducting bid-ask-spreads (net CAR). Both CARs are statistically highly significant and correspond to prior German insider studies. However, when we group our data by index membership, the results change considerably.
- The stocks included in the DAX, on average, have normal returns after insider purchases, with or without taking transaction costs into account. The 20-day net CAR is 0.45% and statistically insignificant. Our interpretation is that for stocks included in the DAX the information asymmetry between insiders and the best informed outsiders is typically small and/or insiders do not exploit their non-public information or special insights, at least not in a detectable way.
- The stocks included in the MDAX and the SDAX have positive abnormal returns after insider purchases. Before transaction costs, the 20-day mean CAR is around 2% for both indices. After deducting the bid-ask spread the CAR is 1.61% for the MDAX and 1.15% for the SDAX, both statistically significant. Our cross-sectional regressions reveal that only the results for the SDAX seem to be robust and cannot be explained by the included control variables.
- For the stocks in the TecDAX we find very high abnormal returns after insider purchases. After deducting the bid-ask spread, the 20-day average abnormal return is 4.62% (highly statistically significant). The high and statistically significant CARs for TecDAX insiders are confirmed by several robustness checks. For an important index of the German stock market we can formally reject the hypotheses of strong-form and semi-strong form efficiency. It also suggests that the relevant regulations and their enforcement can be improved.
- The stocks not included in the mentioned indices (OTHERS) have normal returns after insider purchases (-0.50%) due to their higher bid-ask spreads. The information asymmetry, measured by the abnormal returns before spreads are deducted, is similar to the MDAX and the SDAX.
- When we calculate average CARs for specific insiders, we find some evidence for Seyhun's (1986) information hierarchy hypothesis. However, the cross-sectional regressions we use as robustness checks reveal that this result can be captured by the control variables. Here we can confirm the prior studies by Betzer/Theissen (2009) and Dickgiesser/Kaserer (2010) that the different insider types seem to have similar CARs.

[2] The numbers given are equal-weight averages and abnormal returns are calculated by using a size/industry adjustment.

This result is in contrast to Wang/Shin/Francis (2012) and Knewtson/Nofsinger (2013) who find for the U.S. that CFO trades reveal more informational content than CEOs.

For the 4,061 sales in our final sample, the regression based models (e.g. market model, three-factor model) produce negative and statistically significant CARs, while the non-regression-based models (market adjusted, characteristic based adjustment) typically produce insignificant CARs close to zero. When we use our most preferred abnormal return model, which is based on a size/industry adjustment, we neither find significant equal-weight nor €-volume-weight CARs net of bid-ask spreads. This result is in line with the results of Stotz (2006) and Dickgiesser/Kaserer (2010). The index-specific CARs are also mostly close to zero and insignificant. In the cross-sectional regressions all are insignificant. We therefore report our results for sales only in the appendices and focus on insider purchases.

Due to the traditional long delay between the insider transaction and its publication, the two questions ‘Do insiders trade profitably’ and ‘Can investors make profits by imitating their trading behavior’ often have been analyzed separately. In the U.S. since 2003 and in Germany since 2004, insiders are required to report their trades immediately (U.S: two days, Germany five days). For our sample of German insider transactions, we find a mean delay of only two days. Consequently the 20-day CARs for imitators are a bit smaller than for insiders, but all of our main results hold for both the transaction and publication day.

The short delay between the transaction and its publication raises the possibility that positive CARs are not the result of an informational advantage of insiders but rather result from the erroneous beliefs of imitators that insiders have an informational advantage. We assume that such erroneous beliefs would not survive in the long run and that positive gross CARs are a sign of information asymmetry.

We also contribute to the literature by showing how methodological variations can affect the results and inferences drawn from the data. In recent years in the U.S., considerable progress has been made in refining the standard short-term event study methodology as described in Campbell/Lo/MacKinlay (1997). Important refinements include: value-weight averages, alternative abnormal return models, winsorizing, cross-sectional regressions, and test statistics. When we present our results for the full sample, we focus on the question how do these methodological details affect the results. Here our main conclusions are:

- When we weigh transactions equally, winsorizing affects the magnitude and the statistical significance of the CARs considerably. When weighting by €-volume, winsorizing does not affect the level and the statistical significance of the CARs.
- We can confirm Ahern’s (2009) conclusion: In specific contexts regression based abnormal return models produce very different mean CARs to characteristic based models. As a consequence, we base our conclusions, especially those regarding sales, on size/industry adjusted returns.

The remainder of this paper is as follows. Section 2 reviews the insider trading literature and regulation in the U.S. and Germany. Section 3 illustrates the relation between bid-ask spreads and index membership for Germany. Section 4 describes our data sources, explains how we constructed our sample, and discusses the characteristics of our final sample. Section 5 describes the methodology. The results for the full sample are presented and discussed in Section 6. Index- and insider-specific results for purchases are presented in Section 7. Section 8 investigates the TecDAX in more detail. The final Section 9 contains our concluding remarks.

2. Insider Regulation in the U.S. and Germany, Literature on Insider Profits

The behavior of stock prices around transactions by the directors of a company or by other persons that may possess insider information (that is non-public) has been analyzed in a large number of empirical studies, initially focusing on the U.S., more recently also on the U.K. and many other countries. This is an important topic not only for investors who may base their investments on insider trading data, but also for legislators and regulators. If insiders of publically traded companies profit from the non-public information they have, this violates the law in most countries. In any case, it violates basic notions of fairness and may undermine public confidence in our stock markets. On the other hand, insider trading based on non-public information may make the markets more efficient, which is desirable from a social perspective.[3]

Declaring insider trading based on non-public information illegal may not be sufficient to considerably reduce or eliminate profitable insider trading. The ways in which the law is enforced and the penalties associated with violations of the law probably play an important role in curtailing illegal insider transactions. One key regulation is the obligation to publicly disclose executed transactions.

2.1 U.S. Insider Regulation and Literature

In the U.S., corporate insiders of publically traded companies have been required to report their transactions to the Securities and Exchange Commission (SEC) since 1934, which publishes them.[4] Probably this has reduced the profits associated with illegal insider trading considerably, but it has not eliminated them totally. Lorie/Niederhoffer in 1968 conclude, “proper and prompt analysis of data on insider trading can be profitable.” This result was confirmed by a number of subsequent studies (notably Jaffe (1974), Finnerty (1976)), which may have induced U.S. lawmakers to tighten the enforcement and to increase the penalties.

Seyhun (1986) argues that insider trades and their imitation by outside investors are associated with transaction costs, especially bid-ask spreads, which in case of small firms may be high. He concludes that when transaction costs are taken into account, insiders’ abnormal returns are much lower than those reported in the earlier studies, and that the abnormal return on imitation strategies is negative. Rozeff/Zaman (1988) reach similar conclusions for the NYSE.

[3] Bhattacharya (2014) discusses the arguments for and against insider trading.

[4] Lorie/Niederhoffer (1968) describe the institutional details until the mid-sixties, Brochet (2010) discusses the recent changes in the reporting requirements in detail. Fidrmuc/Goergen/Renneboog (2006) compare the U.S. and the U.K.

Lin/Howe (1990) find for the OTC Market that, "bid-ask spreads are sufficiently high to preclude insiders from realizing positive abnormal returns from an active trading strategy."

One of the important law changes in the U.S.[5] was the Sarbanes Oxley Act (SOX), which became effective in August 2002. Before this date insiders had to report their open market transactions within ten days after the close of the calendar month in which the transaction had occurred, since then within two business days. These actions and the introduction of internal policies relating to insider trades by most exchange traded firms were very effective. Lee/Lemmon/Li/Sequeira (2011) focus on the timing and forecasting ability of the insiders and do not take transactions cost into account. They conclude that abnormal returns following insider trading have completely disappeared since SOX became effective. This seems a bit overstated, however, since a number of studies based on post 2002 data have found that corporate insiders still obtain economically and statistically significant abnormal returns, although only in very specific situations. Typically these situations are hard to exploit by non-professional investors.[6]

2.2 German Insider Regulation and Literature

In U.S. and U.K. studies, the term 'insider trading' typically refers to transactions by board members in securities of the company they run. This paper follows this definition. In Germany, however, the term Directors' Dealings is more common for such transactions, since the law of 1994 classifies transactions by all individuals which had access to private information that may affect a company's stock price as insider transactions. As a consequence, transactions by firm employees that are not board members and the transactions by external advisors may also be classified as insider transactions, which are punishable by the law.

The German law to publicly disclose executed insider transactions came into force on July 1, 2002 by the inclusion of § 15a in the Securities Trading Act (Wertpapierhandelsgesetz, WpHG), which was part of the fourth Financial Market Development Act (4. Finanzmarktförderungsgesetz). Before § 15a WpHG was introduced, there was a similar private regulation by the Frankfurt Stock Exchange (FSE) for stocks listed in the Neuer Markt. Companies in this segment were required to publish the transactions of their board members within three days (Deutsche Börse AG (2001)).[7]

Paragraph 15a WpHG requires board members and their first-degree relatives to disclose their trading activity and to notify the Federal Financial Supervisory Authority (Bundesanstalt für Finanzdienstleistungsaufsicht, BaFin) about their transactions (Baur/Wagner (2002)). With the insider trading law of 2002, insiders were required to publish their transactions im-

5 Other important law changes are the Insider Trading and Securities Fraud Enforcement Act of 1988, which increased the maximum jail term to ten years, the Stock Enforcement Remedies, and the Penny Stock Reform Act of 1990, which effectively made top managers responsible for violations by employees of their firm.

6 Wu (2014), e.g., analyzed brokerage closure-related terminations of analyst coverage, which increased information asymmetry and allowed insider profits. Ravina/Sapienza (2010), Cohen/Malloy/Pomorski (2012), Betzer/Gider/Metzger/Theissen (2014), among others, focus on specific events, types of firms and insiders and/or on specific situations, and typically find significant abnormal returns.

7 Rau (2004) studies the insider transactions in the Neuer Markt.

mediately ("unverzüglich"). No report was necessary if within 30 days the accumulated trading volume was below €25,000.

As a consequence of the introduction of the Market Abuse Directive by the European Union in 2003, the German insider trading law was changed on October 30, 2004. Important changes were the reduction of the reporting limit to €5,000 (cumulated over a year) and the reduction of the reporting period to five working days (Assmann/Schneider (2009)). Also, the group of insiders covered by the law was further broadened to persons with noticeable managerial decision power that have access to insider information, and to household members of an insider who have a close relationship.

The WpHG stipulates that insider trading is punishable by a term of imprisonment of up to five years or a fine (§ 38 WpHG). Investigations can only be started by the responsible regulator, the BaFin. It launched 50 new formal investigations in 2014, 42 in 2013, and 26 in 2012 (BaFin (2015)). If a suspicion hardens, the BaFin reports it to the public prosecutor in the town where the accused lives. This recently occurred less than 35 times per year. After the legal procedures end, the public prosecutor reports back to the BaFin, typically after several years. In 2014, the BaFin received 46 such notifications. In 39 of these, the proceedings were stopped by the public prosecutors, in five cases they were stopped after the accused agreed to make a payment. Only two cases ended in a court of law. It seems that there were no prison terms in 2014 and 2013. In 2012 there were two suspended prison terms, one for 18 months, and one for 24 months.[8] These numbers suggest that the enforcement of the laws may not be strong enough and that the penalties for violations of the law may be too light. This view is also supported by Will/Pies (2014), e.g., who argue that Europe has in comparison to the U.S. a regulatory deficit in the fight against undesirable insider trading.

Most early studies based on German data do not take transaction costs into account. Using the standard short-term event study methodology they find for insider purchases statistically significant average CARs from the purchase day to day +20 of more than 2%. For example, abnormal returns reported by Heidorn/Meyer/Pietrowiak (2004) are 3.79% (investigation period is from July 1, 2002 to March 9, 2004). For nearly the same time span Klinge/Seifert/Stehle (2005) report 2.29% and Betzer/Theissen (2009) 3.6%. Stotz (2006) reports 2.73% (July 1, 2002 to July 7, 2003). There is no clear tendency that the CARs are lower when longer or more recent time periods are studied. Dymke/Walter (2008) find 4.38% (July 1, 2002 to April 30, 2005) and Schüssler (2010) 2.45% (July 1, 2002 to July 31, 2009).

For sales the standard CARs reported in existing studies are: Heidorn et al. (2004): -2.99%, Klinge et al. (2005): -7.41%, Stotz (2006): -2.85%, Betzer/Theissen (2009): -3.54% and Schüssler (2010): -2.82%.

To our knowledge there are only two German studies that include transaction costs. Stotz (2006, p. 460) assumes a round trip transaction cost of 1%. For all purchases he finds that these costs reduce insider CARs to 1.73% and imitator CARs to 1.81%, both are statistically

[8] See Jahresbericht der Bundesanstalt für Finanzdiensleistungsaufsicht (BaFin) 2014, p. 222. See also the newspaper report in "Die Welt" on Jan. 20, 2012: "Den Börsenhaien wird das Handwerk gelegt".

significant. For all sales he reports -1.85% and -1.20%, both insignificant. He notes that during the time period he analyzes only transaction volumes exceeding €25,000 had to be reported. When he focuses on those, the CARs were lower and insignificant for both purchases and sales, insiders and imitators. When he looks at stock purchases involving companies larger than €100 million he obtains a net CAR of 2.75% for insiders and 3.71% for imitators, both which are highly statistically significant. For sales the estimates are again lower and insignificant. The statistically insignificant CARs for sales may be due to the small number of observations. Stotz finally concludes that "[o]utsiders who copy the transactions of insiders can achieve nearly the same abnormal returns […] even after transaction costs". While Stotz states that the round-trip transaction cost of 1% is a conservative estimate, our estimates suggest that it is too low (see Section 3). The procedure of Stotz (2006) also ignores the negative monotonic relationship between firm size and bid-ask spreads (Stoll/Whaley (1983)).

Dickgiesser/Kaserer (2010) on the other hand, find that for both purchases and sales imitators of insider transactions cannot make arbitrage profits when more realistic bid-ask spreads are used. They look at the universe of all transactions in a very similar way as we do. We discuss their procedure in detail in Sections 5.2.

In summary, the results of existing studies of insider purchases and sales that do not take transaction costs into account are very similar to comparable studies focusing on the U.S. in the years prior to 1990, that is, prior to the years in which insider regulation in the U.S and its enforcement became stricter. Transaction costs reduce or even eliminate the profits insiders and imitators can achieve.

3. Index Membership and Bid-Ask Spreads in Germany

The part of the FSE that is regulated by national laws enacted on the basis of Directives of the European Union has two levels of transparency since 2003: Firms that choose the higher transparency standards are listed in the Prime Standard, the others are listed in the General Standard.[9] Since 2007 only a single segment that is regulated by national laws exist, the 'Regulierter Markt'. Firms that are in the Prime Standard and choose Continuous Trading as their trading or market model[10] are eligible to be included in the non-overlapping 'DAX' "selection" index system. The DAX includes the 30 largest German stocks, the MDAX the 50 next-in-size non-technology stocks, and the SDAX the next-in-size 50 non-technology stocks. The TecDAX combines 30 technology stocks not included in the DAX. The largest German stocks have a market capitalization of more than €50 billion, which is 1,000 times larger than the market capitalization of the smallest stocks in the Prime and General Standard. As of December 2012, the 30 stocks in the DAX account for more than 63% of the market capitaliza-

9 For these and other details see Stehle/Schmidt (2015).

10 Stocks that are traded continuously have to fulfill very high liquidity standards. Typically the liquidity is supported by one or more market makers, that is, 'Designated Sponsors'. For these stocks an Open Order Book exists, which is freely available on the Internet to all market participants. It contains the 10 best bid and the 10 best ask prices.

tion of all German stocks in Frankfurt's Regulierter Markt. All stocks listed in the DAX, MDAX, SDAX, and TecDAX together account for 79%. Seventy-one percent (383 of 543 by December 2012) of all German stocks in Frankfurt's Regulierter Markt are not included in one of the mentioned indices.[11]

A number of recent studies find that the bid-ask spreads for DAX, MDAX, SDAX, and TecDAX stocks differ considerably (Klar/van den Bongard (2008), Rösch/Kaserer (2011), Ernst/Stange/Kaserer (2012)). This is important in the context of our study because we estimate the profitability of German insider transactions by taking bid-ask spreads into account.

Other market models offered within the fully electronic XETRA system which exists since November 1997 include Continuous Auction with a Designated Sponsor, Continuous Auction with a Specialist and One (daily) Auction Only with no liquidity provider. Under the specialist system the order book is closed, only the specialist gets insight. Stocks traded in these market models are typically less liquid than the stocks that are traded continuously and, as a consequence, have typically higher bid-ask spreads. The XETRA has been improved over time and the available market models have changed over time, the Continuous Auction with Specialist model, e.g., was introduced for equities in October 2009. Also, over time, more and more stocks of both transparency levels have migrated to the more liquid market models.

Table 1 presents mean bid-ask spreads of stocks sorted by size and index membership for our final sample of insider purchases.[12] The table reveals that bid-ask spreads are related to both size and the index membership. The bottom line of Panel B shows that mean spreads decrease consistently from 6.46% for the stocks in size decile 2 (smallest stocks in our sample) to 0.31% for the stocks in size decile 10 (largest firms). Within all size deciles, the mean bid-ask spreads are smaller for stocks included in the DAX, MDAX, SDAX, and TecDAX than for stocks in the OTHERS category. This category includes stocks traded in the Prime Standard which are not included in the selection indices and the stocks of the General Standard. Please note that due to our sample selection process there are no trades within size decile one. Nearly all stocks in decile 10 are members of the DAX or the MDAX. The mean spreads of DAX stocks is twice as high for the MDAX members (0.30% vs. 0.15%). In decile 8 the means for the MDAX, SDAX, TecDAX, and the stocks not included in one of the four selection indices, OTHERS are 0.54, 0.77, 0.47, and 1.27.

There are several causes for the observed differences, in addition to the chosen transparency level and trading model. Shleifer (1986, p. 588) raises the possibility that index inclusion leads to closer scrutiny of a firm by analysts and investors and to a greater institutional interest in the stock. This results in higher trading volumes and lower bid-ask spreads. Er-

[11] The large amount of stocks not included in one of the mentioned indices range from very small to large stocks. Some firms do not want to fulfill the requirements of the Prime Standard, and thus are not eligible to be included in the selection indices (e.g. Porsche).

[12] The calculation procedure for the mean bid-ask spreads is described in Section 5.2. The construction of our sample is explained in Section 4.2. We also estimate bid-ask spreads of randomly selected stock-days from the universe of all German stocks listed in the top and middle segment of the FSE and find similar results (not tabulated).

win/Miller (1998), e.g., report empirical evidence for this hypothesis. They find stocks that were not trading listed options experience a significant decrease in bid-ask spreads upon S&P500 addition.

Table 1: Bid-Ask Spreads (%)

This table shows medians and means of estimates of bid-ask spreads for purchases grouped by size and index membership of the event stock. The bid-ask spread estimate is the mean over all available bid-ask spreads (based on midpoint quotes) over twenty days before and after each insider purchase (-20;20), see Section 5.2 for details. The borders for the size deciles are based on monthly data of all stocks listed in the top segment of the FSE. Groups with less than 20 observations are in italics.

	Size Decile										
	1	2	3	4	5	6	7	8	9	10	ALL
					Panel A: Median						
DAX	-	-	-	-	-	-	-	-	-	0.09	0.09
MDAX	-	-	-	-	-	*0.58*	*0.53*	0.43	0.30	0.26	0.28
SDAX	-	-	*4.96*	*2.56*	*1.25*	1.24	0.69	0.67	0.62	0.60	0.68
TecDAX	-	*2.89*	-	*3.98*	*2.38*	0.90	0.56	0.39	0.37	*0.16*	0.44
OTHERS	-	5.70	3.89	2.60	2.19	1.74	1.51	1.11	0.51	1.16	2.07
	-	5.48	3.90	2.60	2.19	1.72	1.34	0.64	0.36	0.15	
					Panel B: Mean						
DAX	-	-	-	-	-	-	-	-	-	0.15	0.15
MDAX	-	-	-	-	-	*0.58*	*1.31*	0.54	0.41	0.30	0.39
SDAX	-	-	*5.00*	*2.62*	*1.54*	1.47	0.85	0.77	0.65	0.71	0.85
TecDAX	-	*2.91*	-	*3.98*	*2.26*	1.23	0.68	0.47	0.39	*0.15*	0.66
OTHERS	-	6.62	4.54	3.04	2.63	1.86	1.78	1.27	0.80	3.90	2.64
ALL	-	6.46	4.54	3.03	2.62	1.82	1.51	0.78	0.48	0.31	
					Panel C: Number of Observations						
DAX	0	0	0	0	0	0	0	0	0	837	837
MDAX	0	0	0	0	0	2	5	91	737	416	1,251
SDAX	0	0	5	19	9	69	227	462	250	55	1,112
TecDAX	0	4	0	2	10	29	51	181	52	6	335
OTHERS	0	89	534	626	866	970	729	170	34	33	4,095
	0	93	539	647	885	1,070	1,012	904	1,073	1,347	

In the context of Germany,[13] the greater institutional interest can be documented by the number of analysts on which the I/B/E/S consensus estimates for earnings are based. For DAX members these are based on 17 or more individual estimates, MDAX 4 to 31, SDAX 2 to 22, and TecDAX 3 to 26. For the stocks not included in one of these indices, consensus estimates often do not exist at all (numbers as of December 2014). Another important point seems to be the number of designated sponsors (liquidity providers). Klar/van de Bongard (2008) show that bid-ask spreads narrow with the number of designated sponsors, especially for the TecDAX and SDAX stocks. The number of designated sponsors is on average 2.56 in the MDAX, 1.64 in the SDAX, and 1.63 in the TecDAX. For the OTHERS category we only observe 1.2 (numbers as of June 2011).

[13] See also Betzer/Van den Bongard/Goergen (2013) for the importance of index membership in Germany.

Finally, the focus on the stocks included in the DAX, MDAX, SDAX, and TecDAX is a common procedure in recent German studies. For example, Graf/Stiglbauer (2008), who study the use of expectation management within corporate governance reporting, focus on stocks included in the selection indices. Andres/Betzer/van den Bongard/Haesner/Theissen (2013) limit their analysis of dividend announcements in Germany to firms included in the DAX, MDAX, and SDAX indices because those not included "are very small and have insufficient analyst coverage". Bermig/Frick (2010) also only look at DAX, MDAX, and SDAX stocks.

4. Data and Sample

4.1 Data Sources

Our empirical analysis contains insider transaction data from the BaFin (main source) and Insiderdaten.de,[14] which both maintain publicly accessible databases. We use both databases for two reasons. First, combining both databases improves the accuracy of the data, which allows us to check/filter human typing errors for inaccuracy. Second, Insiderdaten.de's dataset contains, in addition to BaFin's data, the insider's specific position, name, industry sector, index membership, and transaction comments. The names of the insiders and the comment section supply valuable information for our study. Many comments contain additional information, which we use to classify them as a normal or unusual trade (e.g. an insider sold for tax reasons, received stocks from a transfer, exercised rights issues, etc.). Unfortunately, we do not know how stocks are traded exactly, e.g., if the trades are the result of limit orders.

We use daily total return, price, bid, ask, volume, industry/sector classification (Industry Classification Benchmark, ICB), and index data from Thomson Reuters Datastream based on the XETRA system, as well as benchmark and company data from Brückner/Lehmann/Schmidt/Stehle (2015).[15] Datastream sometimes repeats data from the previous day on German official holidays when the FSE is closed (e.g. Easter Monday). We delete these days to avoid a potential bias.

4.2 Sample Construction

We begin the construction of our sample with 35,460 BaFin transactions and 26,528 Insiderdaten.de transactions from July 1, 2002 to December 30, 2012.[16] We first exclude foreign transactions then merge the two databases based on the transaction date, the stock identification code (WKN/ISIN), volume, and price. This results in 28,924 transactions (see Table 2). Next we exclude 5,297 nonstandard stock transactions (stock options[17], rights issue, derivatives, etc.) and 2,510 over the counter transactions. Both filters follow the purpose to create a

[14] Insiderdaten.de is a privately held company that tracks publically known insider security transactions.

[15] We use the data set and benchmark portfolios of 'ALL' with breakpoints from the top segment. The data library is available at http://www.wiwi.hu-berlin.de/professuren/bwl/bb/data.

[16] Insiderdaten.de has fewer transactions because they aggregate transactions from the same insider made on the same day. If an insider reports three purchases on one day, Insiderdaten.de treats them as one trade, whereas the BaFin most likely lists the three transactions separately.

[17] Many are executions of stock options, which are related to (executive) stock option plans.

final sample that consists of *only* plain vanilla stock market transactions. We then exclude 2,653 transactions with stocks not listed in the top and middle segment of the FSE at the day of execution. This filter excludes transactions with stocks listed only on other exchanges. This is desirable because these stocks are not in the stock universe which is used to calculate abnormal returns. It also excludes stocks listed in the lowest segment of the FSE, i.e., stocks listed in the Open Market (formerly named Freiverkehr) and the former Neuer Markt of the FSE. The German law to publicly disclose executed insider transactions does not apply to stocks listed in the Open Market; some insiders seem to voluntary disclose their trades. Also, Stehle/Schmidt (2015) argue that stocks in this segment should not be considered in empirical studies of the German stock market due to the low transparency and high level of criminal activity. We also exclude 121 observations with other errors, i.e., null price/number recordings and trades where the recorded publication day is before the trading day. The filtered sample contains 18,343 observations, which is consolidated to 14,742 because we merge the trades of a specific insider on the same day by calculating the net transaction volume (e.g. a purchase of 1,500 and a sale of 800 stocks equal a net purchase of 700 stocks). We do not merge transactions on the company level because we would lose the information on the specific type of insider (CEO, CFO, etc.).

Next we exclude 577 transactions in which the price reported by the insider is inconsistent with Datastream.[18] We also eliminate 1,448 transactions with illiquid stocks or insufficient return data. Specifically, we exclude transactions if Datastream reports for the event stock no turnover for more than 50 (out of the last 280) trading days before the insider trade or if the total return index contains for more than 140 (out of the last 280) trading days "NA" values or more than 80 (out of the last 280) null returns. We set these relatively complex restrictions since in Germany stocks are not delisted due to insufficient stock exchange trading volume.[19] We also exclude 165 transactions with penny stocks due to their special return characteristics and the criminal activity documented in this area (Stehle/Schmidt (2015)). Here we follow the definition of Stehle/Schmidt (2015) and eliminate all trades with a stock price below €1 and firm's market capitalization below five million. We finally exclude 861 block trades. These are trades with a transaction volume larger than 5% of the stock's market capitalization and trades that probably did not go through the stock exchange because of their large volume (the number of traded stocks by the insider is larger than the total number of traded stocks on all German stock exchanges on the trading day). Additionally, we carefully check all trades

[18] Precisely, we delete all transactions where the price reported to the BaFin, $P_{it}^{Reported}$, for event stock i on insider's trading day $t = 0$ is $\begin{cases} P_{it}^{Reported} > \max\,(P_{it}^{DS} + 0.25, P_{it}^{DS} * 1.1) \\ P_{it}^{Reportet} < \min\,(P_{it}^{DS} - 0.25, P_{it}^{DS} * 0.9) \end{cases}$, where P_{it}^{DS} is Datastream's unadjusted stock price (UP).

[19] Keeping illiquid stocks in the sample may bias the results due to the tendency that betas of these stocks are underestimated in a regression based framework such as the OLS market model (Scholes/Williams (1977), Dimson (1979)). Illiquid stocks may also affect the results of simple market adjusted or characteristic-based abnormal performance measures. For example, when the return on the market/benchmark portfolio is positive (or negative) and the stock due to its illiquidity has a zero return it leads to a biased abnormal performance.

above €10 million. The resulting final sample consists of 11,691 transactions, of which 7,630 are purchases and 4,061 are sales.

Table 2: Filtering and Selection Process of the Final Sample

	BaFin database [July 1, 2002 to December 30, 2012]	35,460
	Insiderdaten.de database [July 1, 2002 to December 30, 2012]	26,528
	Merged database, ex foreign stocks	28,924
-	Non-standard (stock) transactions (rights issues, options, etc.)	5,297
-	OTC transactions	2,510
-	Transactions with stocks not listed in the top and middle segment of the FSE at the time of execution	2,653
-	Other errors (price or number of traded stocks not available, no data in Datastream)	121
	Filtered Sample	18,343
	Consolidated Sample	14,742
-	Transactions with incorrect price recordings (recorded price is out of the range possible on the trading day)	577
-	Transactions with illiquid stocks or insufficient return data	1,448
-	Transactions with penny stocks	165
-	Block trades	861
	Final Sample	11,691
	Purchases	7,630
	Sales	4,061

Empirical studies on German insider trading have large differences in their procedure of filtering the transactions data. Most datasets shrink by 50-70% depending on their selection process. Our dataset is condensed by approximately 67% (from 35,460 to 11,691). The majority of our sample reduction is due to the exclusion of foreign transactions, non-standard stock transactions, and consolidating the sample, which are common filtering procedures in most insider studies. Important improvements in this study are the exclusion of OTC and block transactions as well as transactions with illiquid, penny, and Open Market stocks.

4.3 Final Sample Characteristics

This section provides a brief overview of the characteristics of our final sample and sets the groundwork for further analyses. All statistics are shown in Table 3.

4.3.1 Number of Trades per Year

Panel A shows the total number of purchases and sales for each year from 2002 to 2012. The highest number of transactions reported was in 2008, of which almost 2,054 (91%) were purchases. About 23% (468) of them were recorded between 15 September and the end of October, the time between the collapse of Lehman Brothers and the complications at Hypo Real Estate.[20] Another 19% (396) of the purchases are traded in November and December of that same year.

[20] Lehman Brothers filed for Chapter 11 on September 15, 2008. For information regarding the filing please see http://dm.epiq11.com/LBH/Project (October 25, 2012). Hypo Real Estate Holding AG applied on October 29, 2008 to the Financial Market Stabilization Fund, see press at http://www.hyporealestate.com (October 25, 2012).

Table 3: Summary Statistics for the Final Sample of 11,691 Insider Transactions from 2002 to 2012

For Panel C, the measures for size, book-to-market, and prior return are explained in Table A. 1 of Appendix A. The 0.2/0.4/0.6/0.8 quintiles (Q1: lowest, Q5: highest) are based on the top segment of the FSE. We do not have sufficient data for all event stocks available (e.g. missing return history to calculate prior return) and therefore report some NA values. Index memberships of Panel D are described in Table A. 1 of Appendix A. For the statistics of "Delay", we only consider transactions that have a delay of zero to ten trading days to avoid results that are driven by some large outliers.

Panel A: Number of Purchases and Sales per Year

		2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	Sum
Purchases:	N	183	245	248	594	796	1,102	2,054	602	549	753	504	7,630
	%	(2.4)	(3.2)	(3.3)	(7.8)	(10.4)	(14.4)	(26.9)	(7.9)	(7.2)	(9.9)	(6.6)	(100.0)
Sales:	N	58	369	434	844	676	470	212	325	216	214	243	4,061
	%	(1.4)	(9.1)	(10.7)	(20.8)	(16.6)	(11.6)	(5.2)	(8.0)	(5.3)	(5.3)	(6.0)	(100.0)
Sum		241	614	682	1,438	1,472	1,572	2,266	927	765	967	747	11,691

Panel B: Number of Trades and Average €-volume (k) by Insider Type

		Executive Board Members			Supervisory Board Members						
		CEO	CFO	Other	Chair	Deputy Chair	Other	Through a Company	Household Memb.	Other Insiders	All Insider
N	Purchases	1,281	491	1,653	459	176	1,362	1,351	683	174	7,630
	Sales	341	205	950	229	113	972	357	675	219	4,061
	Pur.+Sales	1,622	696	2,603	688	289	2,334	1,708	1,358	393	11,691
€	Purchases	115.3	58.2	82.3	81.9	62.5	110.5	693.4	579.0	39.9	242.6
	Sales	555.4	352.8	401.4	677.4	104.8	416.2	2,053.9	440.4	824.6	597.3
	Pur.+Sales	207.8	145.0	198.8	280.1	79.0	237.8	977.8	510.1	477.2	365.8

Panel C: Distribution of Event Stock's Firm Size, BM, and Prior Return

		Size				Book-to-Market				Prior Return			
		Purchases: N	(%)	Sales: N	(%)	Purchases: N	(%)	Sales: N	(%)	Purchases: N	(%)	Sales: N	(%)
Quintile	1	93	(1.2)	83	(2.1)	1,410	(19.4)	1,239	(31.7)	981	(13.5)	350	(8.9)
	2	1,186	(15.7)	499	(12.4)	1,654	(22.7)	1,128	(28.9)	1,548	(21.3)	558	(14.3)
	3	1,955	(25.8)	826	(20.5)	1,525	(20.9)	678	(17.4)	1,685	(23.2)	679	(17.4)
	4	1,916	(25.3)	1,032	(25.6)	1,415	(19.4)	526	(13.5)	1,704	(23.5)	998	(25.5)
Quintile	5	2,420	(32.0)	1,596	(39.5)	1,280	(17.6)	333	(8.5)	1,335	(18.4)	1,328	(33.9)
Sum		7,570	(100.0)	4,036	(100.0)	7,284	(100.0)	3,904	(100.0)	7,253	(100.0)	3,913	(100.0)
	NAs	*60*		*25*		*346*		*157*		*377*		*148*	
Sum		*7,630*		*4,061*		*7,630*		*4,061*		*7,630*		*4,061*	

Panel D: Statistics for Purchases and Sales Grouped by the Event Stock's Index Membership

	Purchases:						Sales:					
	N	(%)	€-volume (k) Mean	€-volume (k) Median	# of different Stocks	Delay (avg.)	N	(%)	€-volume (k) Mean	€-volume (k) Median	# of different Stocks	Delay
DAX	837	(11.0)	455	81	42	1.97	566	(13.9)	2,164	521	34	2.46
MDAX	1,251	(16.4)	885	56	77	2.22	703	(17.3)	745	151	70	2.62
SDAX	1,112	(14.6)	141	41	72	1.97	490	(12.1)	313	85	65	2.99
TecDAX	335	(4.4)	153	27	36	2.03	417	(10.3)	668	154	35	2.29
Sum	3,535	(46.3)					2,176	(53.6)				
OTHERS	*4,095*	*(53.7)*	*38*	*14*	*310*	*2.38*	*1,885*	*(46.4)*	*130*	*28*	*231*	*3.05*
Sum	*7,630*	*(100.0)*					*4,061*	*(100.0)*				

There are at least two possible explanations for the large number of purchases from September to December 2008. Insiders were either purchasing more stocks in order to increase public confidence in their company and/or in the stock market in general[21] during a time of financial instability or they simply viewed the magnitude of the fall of their company's stock prices as unwarranted.[22] Also the introduction of a flat rate income tax on income from financial investments (Abgeltungssteuer) and the taxation of capital gains on these investments starting in 2009 may have induced insider purchases (BaFin (2009)). Following potential signals, the relatively small number of insider sales and the strong presence of insider buying in 2008 possibly alleviated additional market declines and contributed to the German stock market's strong recovery. Seyhun (1990) also mentions this point in his study for the U.S. market crash of 1987.

The number of purchases in 2007 is also high, but is only about half of the purchases in 2008. The least amount of transactions is reported in 2002, the year when the insider trading law came into force. It started in July and thus covers only half a year. Note that sales amount only to about one third of all transactions.

4.3.2 Number of Trades and Average €-volumes per Insider Type

Panel B of Table 3 provides statistics for different insider types (they are explained in Table A. 1 of Appendix A). The number of trades by the CFO (696) is much lower than those by the CEO (1,622). Knewtson/Nofsinger's (2013) descriptive statistics for the U.S. also show more trades by CEO's than CFOs. Being the face of the company, and due to the fact that CEO trades are more scrutinized than CFOs trades (Knewtson (2011)), we would expect fewer CEO trades. We also observe that the ratio of the number of purchases to the number of sales is highest for CEOs (1:3.76) and "Through a Company" (1:3.78). The only group for which we observe ratios less than one is "Other Insiders" (174 purchases vs. 219 sales). The average €-volumes[23] traded by the insiders is typically smaller for purchases than for sales, the only exception is the group of household members. Very large €-volumes are observed for "Through a Company" and "Household Member" trades.

4.3.3 Distribution over Size, Book-to-Market and Prior Return Quintiles

Panel C of Table 3 shows the distribution of purchases and sales over size, book-to-market, and prior return quintiles (Q1: lowest, Q5: highest). These statistics are useful as size, book-to-market (Fama/French (1992), (1993)), and prior return (Jegadeesh/Titman (1993), Carhart (1997)) have been shown to passably capture the patterns in stock returns and therefore may play a role in measuring abnormal performance.[24]

[21] Insider confidence signaling has also been acknowledged in U.S. news for the years of 2008 and 2011, see http://articles.chicagotribune.com/2011-09-04/business/ct-biz-0904-bf-insider-selling-20110904_1_vickers-weekly-insider-insider-activity-corporate-insiders, (September 4, 2011).

[22] Schüssler (2010) also documents an increase of insider purchases at the end of 2008.

[23] Reported price multiplied by the number of stocks traded, adjusted by inflation in prices of December 2012.

[24] Other factors are discussed in the literature; however, we focus on the widely known 'anomalies' that might be exploited by insiders.

Our sample contains more trades in medium and large firms (Q2 to Q5) than in small firms. Possible reasons are that the number of insiders increases with firm size and due to the exclusion of transactions with penny stocks and illiquid stocks from our sample.

In the book-to-market section, we find insider purchases are evenly distributed between value and growth firms. Lakonishok/Lee (2001) find for U.S stocks that "[…] insiders tend to be contrarian and prefer to buy value stocks that historically have performed well." Our results for purchases do not convey such a conclusion. On the other hand, we find that a relatively large number of sales take place with low book-to-market firms. Taking the book-to-market ratio as a measure for over- or undervaluation, it may be argued that insiders sell when the stock is overvalued (=low book-to-market). Similarly, Jeng/Zeckhauser/Metrick (2003), expect more insider selling in low book-to-market firms because they are typically younger and "more closely held" than high book-to-market firms. pneumo

The prior return quintiles show a clear pattern for insider sales. About 33.9% of all sales take place when the underlying stock belongs to the group of stocks that went up most in the past twelve months prior to the trade (skipping the most recent month, see the exact definition of variables in Table A. 1 of Appendix A). Only about 8.9% take place when the stock belongs to the group that went up least. Thus, insiders prefer to sell when the stock price has risen considerably, relatively to the rest of the stock universe. This may also support the diversification hypothesis, as the incentive to diversify the portfolio is higher when the insider stock has a large weight in the portfolio. Purchases, on the other hand, do not follow a clear pattern.

4.3.4 Index Specific Characteristics

Panel D of Table 3 contains statistics in which the sample is grouped by the main market indices (DAX, MDAX, SDAX, TecDAX). The OTHERS category is referring to all other stocks not listed in the selection indices. (See Table A. 1 of Appendix A for details about the indices and OTHERS category).

We observe that most insider transactions are made with stocks that are part of the OTHERS category (54% of all purchases and 46% of all sales). This is by far the largest group (see columns three and nine). Hence, our sample (and most likely previous insider trading studies on Germany) includes a large number of trades involving stocks of companies that are small for the German stock market. This is important considering that some of our procedures of cleaning and filtering the insider transactions data (Section 4.2, e.g. the exclusion of 1,448 transactions with illiquid stocks) mainly affect the observations in the OTHERS category. The second highest reporting activity is observed for trades with stocks included in the MDAX (1,251 purchases and 703 sales). It should be considered when analyzing the selection indices that the MDAX and the SDAX include 50 stocks while the DAX and the TecDAX include 30 stocks. Additionally, the number of insiders is much larger for the DAX and MDAX. The insiders of TecDAX stocks reported the least amount of transactions, which only accounts for approximately 6.4% of total trading activity. It is the only index to report more sales than purchases.

The comparison of the transaction volumes of the indices shows for both, purchases and sales, that the median is always much smaller than the mean. This is due to some very large trades. Nevertheless, the difference between the mean and the median varies significantly between the indices. The mean €-volume for purchases made by DAX insiders is €455k (455,000) and the median is €81k. MDAX purchases have an even larger difference (mean €885k, median €56k). Particularly for MDAX trades we observe a large number of outliers with respect to transaction size.[25] Additionally, for purchases and sales, the median €-volume decreases from the DAX to the OTHERS category (except for TecDAX sales). Possible reasons for the decreasing transaction volumes are:

- Insiders of smaller companies usually have lower incomes compared to, for example, DAX insiders, and therefore do not have as much money to invest. Insiders of larger companies are highly monitored and sensitive to the signals they give; therefore, they tend to execute fewer trades (although in larger amounts).
- Insiders of larger companies could possibly purchase in larger amounts to gain more control of the company they run (Jeng et al. (2003), section five A).
- Larger firms may restrict insider trading or impose blackout periods. Consequently, they possibly trade in higher volumes when it is allowed.[26]

Also, when comparing sales and purchases it is evident that sales usually have much larger volumes then purchases. Insiders on average purchase stocks more often than they sell, however when they sell, they do it in higher average volumes. This seems reasonable as sales usually are interpreted as negative signals and insiders probably try to avoid this. Arguments for diversification and liquidity can also be made since insiders typically own a large stake (compared to other investments) of their firm (see also Lakonishok/Lee (2001) and Jeng et al. (2003) for the U.S. and Klinge et al. (2005) for the German market).

Panel D of Table 3 also reports the number of different event stocks and the average reporting delay for each index. The number of different event stocks in each index is higher than the number of equities included in each index since stocks enter and exit the indices (e.g., we have purchases involving 42 DAX stocks, while at any time only 30 stocks are in the DAX). The large number of different event stocks in the OTHERS category (310 in the purchase sample and 231 in the sales sample) again shows that our sample consists of many insider transactions with small stocks. Altogether, the final sample consists of 516 different stocks that belong to 504 firms (12 dual-class firms with transaction in both, common and preferred stocks).

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[25] Appendix F lists all transactions larger than €10 million.

[26] In comparison to the German law where insiders can trade *whenever* they want, the London Stock Exchange Model Code prevents UK insiders from trading during certain time periods surrounding earnings announcements. Sivakumar/Waymire (1994) states some U.S. companies have their own policies surrounding earnings announcements. Please see Bettis/Coles/Lemmon (2000) p. 202 for trading volumes during normal trading days vs. blackout periods.

Average reporting delay is the number of trading days that elapse from the execution to the publication of insiders' transactions. Overall, insiders tend to publish their trades more quickly when purchasing stocks. However, there are minor differences between the indices. DAX and SDAX insiders have the shortest delay when purchasing stocks (1.97 days). When selling, the longest delay is by insiders of OTHERS (3.05 days), followed by SDAX insiders (2.99). Note that Betzer/Theissen (2010) find for Germany no relation between reporting delay and abnormal returns post publication day.

5. Methodology

In event studies focusing on the U.S. market a number of new methods to calculate abnormal returns have been suggested and implemented, especially multi-factor models and characteristic based models. Existing German insider studies typically use the traditional methods, market adjusted returns and market model adjusted returns. To see whether the model choice affects the results and to compare our results with prior studies, we initially calculate abnormal returns in a number of ways. Section 5.1 shows the alternative models and also describes the testing procedures.

In most event studies transaction costs are not taken into account. A standard, commonly accepted procedure to take them into account in event studies does not exist. Data availability and data quality play an important role in the choice of an appropriate procedure. Both have improved over time but still are not ideal. We follow the most common procedure in taking transaction costs into account, which consists of three separate steps. In the first step, abnormal returns and cumulative abnormal returns are calculated in the traditional way, that is, without considering transaction costs. This results in a (gross) CAR for each individual event, here each insider transaction. In a second step, transaction costs in percent are estimated (Section 5.2). In the third step, the estimate for the transaction cost is deducted from the gross CAR to obtain the net CAR, that is, the CAR that takes transaction costs into account (Section 5.3).

In recent U.S. event studies, value-weight CARs are often presented in addition to equal-weight CARs. We think this is also appropriate in our context (Section 5.4).

To check the robustness of our results we additionally consider winsorizing abnormal returns. They can be anomalous for specific observations due to, e.g., data problems and influence the mean CAR considerably (Section 5.5).

5.1 Estimation and Testing of Abnormal Returns Without Transaction Costs

In our first step we calculate gross abnormal and CARs according to the standard procedure discussed in Campbell/Lo/MacKinlay (1997). We calculate abnormal returns over an event window of 41 days, which includes the insider trading (or publication) day along with the 20 days before and 20 days after the event. Coefficients in model (2), (3) and (4) are estimated over 220 trading days before the beginning of the event window (overall length of 261 trading days). The gross (abnormal) performance is based on closing prices[27] (Datastream's total return index, adjusted for corporate actions).[28]

We alternatively use the following models to calculate abnormal returns:

(1) Market adjusted returns ($\alpha = 0$; $\beta = 1$). We apply two indices, the (1.1) CDAX and the (1.2) index of the event stock (e.g. if an insider trades an MDAX stock, the MDAX is the benchmark).[29]
(2) Market model adjusted. (Same indices as in (1.1) and (1.2).)
(3) Fama/French (1993) three-factor model.
(4) Carhart (1997) four-factor model.
(5) Characteristic-based abnormal returns (Daniel/Grinblatt/Titman/Wermers (1997)). A portfolio of stocks with similar characteristics as the event stock (size, book-to-market, prior return, and/or industry) is the benchmark. We use (5.1) size/prior return and (5.2) size/book-to-market matching, where the benchmark portfolio is selected from 16 equal-weight portfolios (4x4), first formed on size, then on prior return or book-to-market (dependent sort).[30] We also estimate abnormal returns based on a (5.3) size/industry matching. The benchmark is an equal-weight portfolio of ten stocks sharing the same industry and having the nearest size to the event stock.

Altogether we use nine alternatives to calculate abnormal returns. An important result of this exercise is that for purchases all nine alternatives produce very similar CARs. For sales, on the other hand, they produce very different CARs. This result confirms Ahern's (2009) conclusion. He documents significant statistical errors for the market model and multi-factor model adjusted returns in the specific situations he looks at. Specifically, he documents false statistical significance for the often preferred 'OLS market model', especially for samples containing small stocks (see also Coutts/Mills/Roberts (1994)). Due to the evidence presented by Ahern (2009), we rely on the results of the non-regression based models, especially the characteristic-based models.

To facilitate the presentation of our evidence, we only report the results based on size-industry benchmarks in our main tables. Among the three characteristic-based models we consider, we prefer the size/industry benchmark because:

- Moskowitz/Grinblatt (1999) show that individual stock momentum (prior return) can be explained by the performance of the corresponding industry. Thus, we possibly are able to capture both stock momentum and industry related effects.

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[27] An exception is $t = 0$, the insider trading day, for which we use the reported trading price for the return calculation. For purchases, the mean raw return for $t = 0$ is 0.15% (*t*-statistic 4.78), for sales 0.16% (*t*-statistic 3.70).

[28] Lease/Masulis/Page (1991), who analyze market microstructure impacts on abnormal returns, propose to calculate returns from midpoints of closing bid and ask quotes when order imbalances are suspected. We do not think this is a problem in our context and use closing prices in the calculation of the gross abnormal returns and CARs.

[29] For stocks in the OTHERS category we use Datastream's "MidCap market index" for Germany.

[30] Daniel et al. (1997) use benchmark portfolios based on size, book-to-market, and prior return (3 dimensions). Since the German stock market has a much lower universe of listed stocks, a three-dimensional sort makes it virtually impossible to have a reasonable number of stocks in each portfolio.

- Firms within the same industry are most likely better benchmarks than firms with similar book-to-market ratios or other characteristics.
- The benchmark portfolio of the ten stocks does not contain the event stock, which is not true for our size/prior return and size/book-to-market matched approach. The latter 16 (4x4) portfolios contain all stocks from the top and middle segments of the FSE (see Brückner et al. (2015)).

As a consequence, all results presented in the main tables are based on the size/industry benchmark. CARs for the other models are shown in Table A. 2 of Appendix B and discussed when comparing our results to earlier work on German insider transactions, which typically calculate market model adjusted returns.

To test if (cumulative) abnormal returns significantly differ from zero we apply the nonparametric GRANK-test proposed by Kolari/Pynnonen (2011). This test procedure tends to be robust against event-induced volatility, autocorrelation of abnormal returns, and event clustering. We also employ the adjustment proposed by Kolari/Pynnonen (2010) that takes cross correlations into account, which may be useful since event windows partly overlap.

5.2 Estimation of Transaction Costs

The second step involves the estimation of transaction costs. In the early papers the estimates for the transaction costs are taken from the prior literature (e.g. Seyhun (1986)). Due to the better data availability today, transaction costs are estimated individually for each observation. This allows the calculation of test-statistics for individual groups as well as employs it in a cross-sectional regression framework.

There are several costs that may be considered when estimating abnormal returns net of transaction costs. Seyhun (1986) and Bettis/Vickrey/Vickrey (1997) include the bid-ask spread plus a commission fee. More recent studies (e.g. Friederich et al. (2002), Dickgiesser/Kaserer (2010)) typically only include the bid-ask spread because it is considered to be the largest part. Additional portfolio or commission costs are usually omitted due to their relatively small amount. These costs also have decreased in the last decade. We follow the most recent studies and include only the bid-ask spread, which makes our approach somewhat conservative.

The literature provides several procedures to estimate bid-ask spreads. A common procedure is to estimate bid-ask spreads from quoted bid and ask prices. Since Datastream provides for each stock daily closing bid and ask quotes, we also consider this approach.[31]

Friederich et al. (2002), who also use a three step procedure in their analysis of UK insider transactions, deduct half of the spread observed on the event day and half of the spread ob-

[31] Datastream seems to provide bid and ask quotes even for stocks not trading continuously. These stocks are typically traded in daily call auctions for which a bid-ask spread is not defined. In June 2011, 444 stocks are in our sample, 63 of them traded only in call auctions (=936 transactions), 381 traded continuously (10,060 observations). However, following Haller/Stoll (1989) and Kehr/Krahnen/Theissen (2001), implicit bid-ask spreads also exists for stocks trading in a call auction market. We thank an anonymous referee for pointing this out.

served on the (twenty-day) post event day from the gross CAR. With this procedure we would lose 349 of our observations because Datastream does not always provide the bid and ask quotes needed for its implementation.

Dickgiesser/Kaserer (2010), in the second part of their paper, analyze a zero-investment arbitrage trading strategy: imitators are assumed to take a long position in the company's stock on the day of the announcement, which they hedge by an opposite position in the CDAX. After 20 trading days both positions are liquidated. The return on the position in the stock is thus based on the ask quote on the event day (=publication day) and the bid quote on the (twenty-day) post event day. Thus, their gross CARs are CDAX adjusted buy and hold returns. In short term event studies it does not matter much whether CARs are obtained by adding up abnormal returns or by a buy-and hold calculation. However, and similar to the procedure of Friederich et al. (2002), we would lose 349 of our observations.

To keep the observations in the sample and to reduce a potential bias from using one-day bid and ask quotes that could be anomalous, we estimate a stock's individual bid-ask spread (in %) by taking the mean of all available percentage bid-ask spreads (based on midpoint quotes) in event time (-20;20). This procedure allows missing daily bid and ask quotes. On average 39.98 of the 41 days enter the mean, but a number of mean spreads are only based on a few observations. For the 320 observations of which we could not obtain bid-ask quotes at all, we assign the mean bid-ask spread of stocks that are in the same size decile. However, given our large number of observations our, Friederich et al.'s (2002) and Dickgiesser/Kaserer's (2010) approach should lead to similar results.

Note that a potential bias from unusual spreads in event time is unlikely. Chung/Charoenwong (1998) find for the U.S. no evidence that bid-ask spreads change around insider trading days. Also, since bid-ask spreads tend to be higher in the beginning of a trading day and decrease throughout the day (see e.g. Groß-Klußmann/Hautsch (2013)) our approach of using closing bid-ask spreads is conservative.

A number of studies do not use bid-ask data but estimate the bid-ask spreads using the procedures proposed by Roll (1984), or more recently by Corwin/Schultz (2012). Our estimates based on bid-ask data are much more in line with prior studies on bid-ask spreads in Germany than the estimates we obtain when implementing the methods of Roll and Corwin/Schultz. In addition, Theissen (2000) finds that Roll's serial covariance estimator is inappropriate for Germany. Therefore we rely on the estimates based on quoted bid and ask prices.

5.3 Estimation of Abnormal Returns With Transaction Costs

In the third step we deduct the transaction cost estimate, this is the bid-ask spread, from the standard gross CAR and obtain the net cumulative abnormal return (net CAR):

$$CAR_{m,i}^{net}(\tau_1,\tau_2) = \left[\sum_{t=\tau_1}^{\tau_2} R_{i,t} - BR_{m,t}\right] - \begin{cases} Spread_i & if\ Purchase \\ -Spread_i & if\ Sale \end{cases}$$
$$= CAR_{m,i}^{gross}(\tau_1,\tau_2) - \begin{cases} Spread_i & if\ Purchase \\ -Spread_i & if\ Sale \end{cases}. \quad (1)$$

$CAR_{m,i}$ is the cumulative abnormal return of event stock i (the stock undergoing the event of being purchased or sold by an insider) over a time period τ_1 to τ_2 (see e.g. Campbell/Lo/MacKinlay (1997)) under model m (see Section 5.1), $R_{i,t}$ is the return of event stock i on day t, $BR_{m,t}$ is the benchmark return under model m on day t, and $Spread_i$ is the estimate for the event stock's i bid-ask spread as explained above.

It may be argued that addressing transaction costs only at the stock level is one-sided because the benchmark is subjected to transaction costs too. In fact, and depending on the stock and the volume traded, commissions, price impact costs, taxes, etc. can in addition reduce profits. While this is true, we only consider bid-ask spreads since this cost is generally the largest cost, which is a conservative estimate and negligible for index/benchmarks products. Also, we argue that insiders shift their wealth from the market portfolio/benchmark to the stock of the company they run (vice versa) and bear the transaction costs, which the insider would not have faced if he or she had stayed invested.

5.4 Weighting of Observations

Existing German event studies usually present only equal-weight CARs. This procedure does not reflect the absolute or relative transaction volume. An insider trading €1,000 on one day and €9,000 on another day earns 1/10 of his total return from the first trade and 9/10 on the second trade. When evaluating the returns insiders earn from their stock market transactions it is reasonable to consider a weighting procedure that takes the transaction volume into account. We thus calculate €-volume-weight CARs in addition to the standard equal-weight CARs. The €-volume (or €-vol) is the reported price multiplied by the number of stocks traded, adjusted by inflation in prices of December 2012.

The final sample consists of a few extremely large transactions that may influence the €-volume-weight result considerably. In the purchases sample, the two largest trades account for one third of the total €-volume.[32] The three largest transactions in the sales sample account for one fifth of the total €-volume. In order to reduce the influence of these large transactions, we winsorize the €-volumes at the 97.5% level.[33]

[32] Appendix F lists all transactions larger than €10 million.

[33] A transaction may be medium-sized in relation to the very large transactions in the total sample but still be very large in a specific sub-sample of only a few observations. To account for this, we winsorize €-volumes within each group or sub-sample that is analyzed.

5.5 Winsorizing Abnormal Returns

To check the robustness of our results we additionally consider winsorizing returns.[34] Winsorizing could alternatively be applied to raw returns, abnormal returns (residuals), or to CARs. In case it is applied to the abnormal returns it could be used in the estimation and/or the event window. The way and the level in which it is used vary in the literature. Cowan/Sergeant (2001) suggest to winsorize buy-and-hold abnormal returns at ±3 standard deviations. Brav/Lehavy (2003) winsorize monthly raw returns at the 2% and 98% levels, while Ikenberry/Ramnath (2002) winsorize at the 1% and 99% levels. Bailey/Karolyi/Salva (2006) winsorize all residuals at the 1% and 99% levels. We think the latter approach is preferable because it eliminates outliers in event and estimation time in the same way. Only winsorizing the time series of CARs may introduce biased GRANK-test statistics since the test also relies on the residuals in estimation time. Since there is no consensus on which level (if any) winsorizing should be applied, we winsorize daily abnormal returns (residuals in event and estimation time) on three different levels: no winsorizing at all, winsorizing in both tails at the 1% and 99% levels, and at 2% and 98%. We then continue our process by calculating and testing the CARs, etc.

6. Results for the Full Sample

We first analyze CARs over twenty days post transaction and publication day for our full final sample. Table 4 reports CARs for purchases and sales, gross and net of the bid-ask spread, using equal-weights and €-volume-weights, based on non-winsorized and winsorized abnormal returns. Returns are adjusted by the return of a portfolio of non-event stocks sharing the same size and industry (size/industry, see Section 5.1). We start our discussion by looking at the returns for insiders (Section 6.1), then at the returns for imitators (Section 6.2).

6.1 Returns for Insiders

Panel A of Table 4 reports 20-day CARs post insider transaction day, that is, the average (abnormal) returns insiders typically earn from their trades. These are usually negative for sales and positive for purchases.

6.1.1 The Informational Content

Column two (purchases) and column six (sales) contain the standard equal-weight CARs (before deducting bid-ask spreads). These results report the informational content of insider transactions. The numbers in line one are based on returns that are non-winsorized.

We obtain for purchases a standard mean CAR of 2.69% (t_{GRANK}-statistic 18.75, t_G hereafter) over twenty days post insider transaction day. This result is very similar to the results of the existing studies (see Section 2.2), which typically use equal-weights and do not winsorize.

[34] It may be debated whether winsorizing in general is appropriate or not (see Kotharia/Sabino/Zach (2005) and Sorokina/Booth/Thornton (2013)).

All other models discussed in Section 5.1 produce very similar results for purchases; see Table A. 2 of Appendix B. We cannot reject the null hypothesis of equal means.[35]

Our result for sales is -1.26% (t_G = -5.52). It differs considerably from the earlier studies on German insider transactions (see Section 2.2). Our CAR, in absolute terms, is less than half of the lowest CAR of the existing studies (-2.85% by Stotz (2006)). However, the normal return model used in earlier studies on German insider transactions is typically the market model. The results in Table 4 are based on a characteristic based adjustment where the benchmark is a portfolio of non-event stocks sharing the same size and industry (size/industry, see Section 5.1). Table A. 2 of Appendix B also reports the results for the market model with the CDAX as the market index. With this model we obtain for sales a CAR of -2.94% (t_G = -11.45), which is fully in line with the earlier studies on German insider transactions.[36]

Table 4: CARs for Insider Purchases and Sales: Full Sample

This table shows CARs gross, $\overline{CAR}^{gross}$, and net, $\overline{CAR}^{net}$, of the bid-ask spread over twenty days post insider trading day and publication day (see Section 5.3). The CAR net of bid-ask spread is $CAR^{net}_{m,i}(\tau_1,\tau_2) = CAR^{gross}_{m,i}(\tau_1,\tau_2) - \begin{cases} Spread_i & if\ Purchase \\ -Spread_i & if\ Sale \end{cases}$. Each transaction's individual CAR is weighted (1) equal or (2) by transaction volume (€-vol, reported price multiplied by the number of stocks traded, adjusted by inflation in prices of December 2012). Transaction volumes are winsorized at 97.5%. Returns are adjusted by the return of a portfolio of non-event stocks sharing the same size and industry (size/industry, see Section 5.1). Results for alternative models are presented in Table A. 2 of Appendix B. For robustness checks, net CARs are also presented with daily abnormal returns (residuals in event and estimation time) winsorized on three different levels: "No" winsorizing at all, winsorizing in both tails at the 1% and 99% levels (1/99), and at 2% and 98% (2/98). Test statistics of the GRANK-test by Kolari/Pynnonen (2011) are given below in parentheses (variance is weighted accordingly for weighting procedure (2)). Asterisks ***, **, * equal a significance level of 1%, 5%, and 10%.

Abnormal Returns winsorized at	Purchases (N=7,119)				Sales (N=3,744)			
	Weighting: Equal		Weighting: €-vol		Weighting: Equal		Weighting: €-vol	
	$\overline{CAR}^{gross}$	$\overline{CAR}^{net}$	$\overline{CAR}^{gross}$	$\overline{CAR}^{net}$	$\overline{CAR}^{gross}$	$\overline{CAR}^{net}$	$\overline{WCAR}^{gross}$	$\overline{WCAR}^{net}$
Panel A: 20-Day Post Trading Day								
No	2.69***	1.06***	2.59***	1.87***	-1.26***	0.03	-0.59*	-0.07
	(18.75)	(9.12)	(10.70)	(8.46)	(-5.52)	(-0.28)	(-1.67)	(-0.50)
1/99	2.34***	0.71***	2.55***	1.83***	-1.85***	-0.56	-0.64**	-0.12
	(7.68)	(2.88)	(8.89)	(6.87)	(-4.65)	(-1.61)	(-1.98)	(-0.78)
2/98	2.05***	0.42	2.36***	1.65***	-1.97***	-0.69	-0.71**	-0.20
	(3.20)	(0.65)	(5.19)	(3.83)	(-3.26)	(-1.51)	(-2.25)	(-1.15)
Panel B: 20-Day Post Publication Day								
No	2.05***	0.43***	1.78***	1.06***	-0.85***	0.41	-0.77**	-0.26
	(10.70)	(3.54)	(5.93)	(4.28)	(-2.89)	(1.02)	(-2.07)	(-0.96)
1/99	1.71***	0.08	1.84***	1.12***	-1.59***	-0.33	-0.81**	-0.30
	(5.22)	(0.73)	(5.34)	(3.65)	(-3.58)	(-0.73)	(-2.30)	(-1.14)
2/98	1.43**	-0.20	1.68***	0.96**	-1.75***	-0.49	-0.86**	-0.35
	(2.04)	(-0.43)	(3.34)	(2.08)	(-2.81)	(-1.05)	(-2.50)	(-1.40)

35 To test whether the differences between the mean CARs are significant we perform a standard Analysis of Variance (ANOVA). We cannot reject the null hypothesis of equal means for all models for both mean (equal-weight, no winsorizing) gross (p-value 0.198) and net (p-value 0.255) CARs.

36 An exception is Klinge et al. (2005), who report -7.41% (see Section 2.2).

The comparison of the CARs for sales obtained with the different models confirms Ahern's (2009) conclusion: In specific contexts regression based abnormal return models (market model, Fama/French 3-factor, Carhart 4-factor) produce very different CARs than non-regression based models (market adjusted, characteristic based portfolios).[37] Nevertheless, the standard CAR under our preferred model of size/industry adjusted returns is -1.26% and highly statistically significant. Hence, based on the informational content German insider transactions convey to the market, our results are consistent (although smaller in magnitude for sales) with prior empirical research.

6.1.2 Insider Profits after Deducting Bid-Ask Spreads

Column three (purchases) and column seven (sales) reports mean equal-weight CARs net of the bid-ask spread. Our sample contains many insider trades involving small and medium size stocks, therefore the bid-ask spread can significantly reduce insider returns. We calculate abnormal returns net of the bid-ask spread by deducting the event stock's individual bid-ask spread from the standard CAR for each insider transaction (see Section 5).

For purchases, the CAR net of the bid-ask spread without winsorizing is 1.06% (t_G = 9.12), which is a reduction of more than 1.6%-points (that is 60%) in comparison to the gross CAR. The difference between the gross and net CAR is equal to the overall mean bid-ask spread we estimate for the purchase sample.[38] Thus the bid-ask spread reduces the profitability of purchases considerably. For sales, the same effect can be found since we estimate a mean bid-ask spread of 1.30%.[39] Here the CAR increases (decreases in absolute terms) from –1.26% to almost zero: -0.03% (t_G = -0.28).

6.1.3 €-Volume-Weight CARs

Existing German event studies usually present only equal-weight CARs. When asking whether insiders (or imitators) trade profitably the transaction size should be considered (see Section 5.4). Columns four and five (purchases) and columns eight and nine (sales) report CARs gross and net of bid-ask spreads using €-volume-weights. For purchases we estimate 2.59% (t_G = 10.70) gross and 1.87% (t_G = 8.46) net of bid-ask spread. For sales, -0.59% (t_G = -1.67) and -0.07% (t_G = -0.50).[40]

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[37] The ANOVA results in a rejection of the null hypothesis of equal means for all models for both mean (equal-weight, no winsorizing) gross (p-value 0.000) and net (p-value 0.000) CARs. Pairwise comparisons of mean CARs using t-tests with pooled standard deviations and correction for multiple testing formally reveal that the mean CARs resulting from the regression based models are (and in all cases) not equal to the non-regression based models and vice versa (results not tabulated).

[38] Deducting the mean bid-ask spread over all observations from the 'standard' mean CAR is equal to deducting the individual bid-ask spread from each observation's standard CAR. Thus the difference between the CARs is always 1.65% points, independent of the normal return model employed. Appendix E contains a plot of the distribution of bid-ask spreads.

[39] The overall mean bid-ask spread for sales is lower than for purchases because a larger proportion of sales was executed in large stocks that tend to have smaller spreads (see Table 3).

[40] The GRANK-test (Kolari/Pynnonen (2011)) is adjusted according to the weights (weighted variance, weighted standardized abnormal ranks).

For purchases, the €-volume-weight CAR net of bid-ask spread (1.87%) is considerably larger than the equal-weight CAR net of bid-ask spread (1.06%), while the gross CARs are similar (2.59% and 2.69%). This finding is due to the tendency that larger transaction volumes are executed by insiders of large stocks that in turn have smaller bid-ask spreads. Or put differently, the €-volume-weight reduces the impact of bid-ask spreads on the average net CAR. For sales, weighting by €-volumes decreases the gross CAR considerably, while the net CAR remains almost unchanged.

6.1.4 Robustness: Winsorizing Abnormal Returns

All results discussed so far were based on non-winsorized returns. Table 4 also contains CARs based on winsorized abnormal returns (lines 1/99 and 2/98).

Equal-weight CARs change considerably when switching from not winsorizing to winsorizing abnormal returns at the 2% and 98% levels. For purchases, the net CAR decreases from 1.06% (t_G = 9.12) to 0.42% (t_G = 0.65), which is now statistically insignificant. For sales, the net CAR decreases (increase in absolute terms) by 0.72%-points from 0.03% (t_G = -0.28) to -0.69% (t_G = -1.51). This result indicates that both samples contain some observations with very large <u>positive</u> CARs. For the purchase sample this result is reasonable, but for the sales sample this is puzzling. One would expect to capture some large negative (and not positive) outliers to smooth the overall CAR.

On the other hand, and most importantly, winsorizing abnormal returns has only a very small impact on the €-volume-weight abnormal performance. The abnormal performance decreases by only 0.22%-points for purchases and by 0.13%-points for sales. This indicates that winsorizing takes place disproportionally in transactions with small €-volumes.

6.2 Returns for Imitators

Panel B of Table 4 reports 20-day CARs post publication day, that is, the average (abnormal) returns imitators typically earn from their trades. These are usually negative for sales and positive for purchases too, but typically smaller than for insiders.

For purchases, the CARs based on the publication are roughly 0.65%-points less than those based on the transaction day. This finding is quite independent from the methodology applied. The equal-weight gross CAR without winsorizing abnormal returns, e.g., decreases from 2.69% to 2.05%, when winsorizing at the 2% and 98% levels it decreases from 2.05% to 1.43%. The €-volume-weight net CAR with winsorized abnormal returns at the 2% and 98% levels decreases from 1.65% to 0.96%, which is still highly statistically significant and again a reduction of roughly 0.65%-points.

For sales, the differences between the CARs for insiders and imitators are smaller than for purchases. The largest difference is between the non-winsorized equal-weight gross CARs, which increases (decreases in magnitude) from -1.26% to -0.85% (0.41%-points). When €-volume-weights are applied, the CARs slightly decrease (increase in magnitude). However, all gross CARs for imitators are negative and statistically significant. All net CARs are close to zero and statistically insignificant.

Based on the economic and statistical significance, the results we obtain for insiders typically also hold for their imitators. CARs that are economically and statistically significant under a selected methodology for insiders are typically also economically and statistically significant for imitators. They only differ in their magnitude.

6.3 Discussion

The most important results in this section relate to methodological issues:

- In our sample of German insider transactions winsorizing matters when we look at equal-weight returns. For purchases, net CARs for insiders and imitators become economically and statistically insignificant. When weighting by €-volume, winsorizing does not affect the level and the statistical significance of the CARs.
- We can confirm Ahern's (2009) conclusion: In specific contexts regression based abnormal return models produce very different CARs than characteristic based models.

In view of the first methodological result we base our conclusions regarding insider and imitators on €-volume-weight CARs. Both profit from their purchases, even when we deduct bid-ask spreads. With purchases, we get very similar results for all abnormal return models. Dickgiesser/Kaserer (2010) concluded that imitators, on average, do not profit. Our result differs because we use €-volume-weights, they only use equal-weights. Since we obtain the same result with or without winsorizing we consider it to be sufficiently robust.

In view of the second methodological result we base our conclusions regarding sales on size/industry adjusted returns: Here average profits exist for insiders and imitators, when transaction costs. When we deduct bid-ask spreads, we do not obtain significant results.

The insignificant net CARs for sales are in line with Stotz (2006) and Dickgiesser/Kaserer (2010). The significant abnormal returns following insider purchases even after bid-ask spreads, for insiders and their imitators are somewhat surprising and ask for a further investigation. We concentrate on purchases in the next sections and from now on report results for sales only in the appendices. Also, since the results usually also hold for imitators, we typically report the results following the publication day only in the appendices.[41]

7. Results for Specific Indices

In this section we first present and discuss net CARs for the different indices and the OTHERS category. As we have already mentioned in the introduction, the mean net CAR for the DAX members and the members of the OTHERS are close to zero. For purchases by TecDAX insiders it is around 5%, depending on the weighting procedure. These and other index-specific results may be caused by different levels of information asymmetry and by

[41] The results can be found in the Appendix G (purchases) and Appendix I (sales).

different levels of transaction costs. In the additional steps of our analysis we check a number of alternative explanations for this and the other index related results.

Another possible explanation of the CAR differences relates to the number and types of insiders. All firms have only one CEO and one CFO. According to Seyhun's (1986) information hierarchy hypothesis these main insiders possess better information about a firm's future than, e.g., members of the supervisory board. Most small firms in our sample have only three supervisory board members, all DAX firms have more than 10, some have 20. If the typical CAR of a CEO purchase is 3%, that of a supervisory board member 0%, a large number of transactions by the latter group may be responsible for the low average CAR by persons which are classified as DAX insiders. Similarly, the index-specific CARs may simply reflect the fact that DAX members have a very large market capitalization compared to the other groups.

In Section 7.1 we look at the index-specific results. In Section 7.2 we group the sample by insider type and index membership. One advantage of a two-way classification is that no assumption about the functional form of the relationship must be made. Another one is that it allows a group-specific comparison of the equal- and €-volume-weight result. In the cross-sectional regressions of Section 7.3 we include a number of additional variables that may affect the CARs.

The results for the transaction day can be found in Table 5. For some subsets our sample contains only a few observations, which is why means are only calculated for those consisting of at least twenty observations. The results after the publication day, this is, the returns to imitators are again smaller, but very similar to those of the insiders and thus are not discussed here and only reported in appendices. We concentrate on net CARs throughout this section because our focus is on the profitability of insider transactions. Also, the CARs discussed are based on winsorized abnormal returns at the 2% and 98% levels to facilitate the robustness of our results.

7.1 Index Specific Abnormal Returns

The bottom line of Table 5 shows that purchases by insiders of DAX firms as a whole have relatively small and statistically insignificant CARs. The equal-weight net CAR is 0.45% and the €-volume-weight net CAR is 0.68%. Our results indicate that insiders of DAX stocks, on average, do not profit from their stock market transactions, which is different from the overall result presented in Table 4. Furthermore, due to the small average bid-ask spread of 0.15% (see Table 1), the results suggest that the informational content of these trades is small (0.45+0.15%=0.60%). Only 51.6% of the gross CARs and 50.8% of the net CARs are positive, see Table A. 3 of Appendix C. Stocks included in the DAX have normal returns after insider purchases regardless of the bid-ask spread. These results could be caused by a low information asymmetry or possibly by the law-abiding behavior of DAX insiders.

Table 5: Equal- and €-Volume-Weight CARs for Insider Purchases Grouped by Insider Type and the Index Membership of the Event Stock

This table shows CARs net of the bid-ask spread (see Table 4 or formula 1, Section 5.3) for insider purchases over twenty days post insider trading day. The sample is grouped by the type of the insider and/or the event stock's index membership. Each transaction's individual net CAR is weighted (1) equal [1/N] or (2) by transaction volume (€-vol*) with outliers in volume winsorized at 97.5% for each group individually, see Section 5.4 for details. Daily abnormal returns (residuals in event and estimation time) are winsorized at the 2% and 98% levels. The €-volume is insider's transaction volume (reported price multiplied by the number of stocks traded, adjusted by inflation in prices of December 2012). Returns are adjusted by the return on a portfolio of ten stocks sharing the same size and industry as the event stock (size/industry, see Section 5.1). Test statistics of the GRANK-test by Kolari/Pynnonen (2011) are given below in parentheses (variance is weighted accordingly for weighting procedure (2)). Asterisks ***, **, * equal a significance level of 1%, 5%, and 10%.

	DAX			MDAX			SDAX			TecDAX			OTHERS			ALL		
	N	Equal	€-vol*	N	Equal	€-vol*	N	Equal	€-vol*	N	Equal	€-vol*	N	Equal	€-vol*	N	Equal	€-vol*
Executive Board Members																		
CEO	102	0.65	1.16	166	1.18**	3.47***	175	2.48***	3.43***	44	4.42***	3.71*	756	-1.76**	-0.30	1,243	-0.36	1.88***
		(1.13)	*(1.26)*		*(2.06)*	*(2.97)*		*(4.48)*	*(3.62)*		*(3.32)*	*(1.67)*		*(-2.18)*	*(-0.31)*		*(-0.14)*	*(3.38)*
CFO	56	1.13	1.47	114	-0.71	-2.09	65	2.53**	1.71	38	4.07***	3.99	210	0.08	1.03	483	0.66	0.35
		(0.73)	*(0.68)*		*(0.19)*	*(-0.69)*		*(2.04)*	*(1.01)*		*(2.72)*	*(1.45)*		*(-0.68)*	*(0.46)*		*(0.94)*	*(0.96)*
Other	362	0.49	0.82	301	2.22***	2.18**	158	2.62***	-0.13	52	4.45***	0.74	746	-1.54	-0.87	1,619	0.21	0.72
		(1.06)	*(0.91)*		*(3.10)*	*(2.46)*		*(3.09)*	*(-0.65)*		*(3.84)*	*(0.66)*		*(-1.58)*	*(-0.82)*		*(0.67)*	*(1.39)*
Supervisory Board Members																		
Chair	23	0.19	0.47	45	1.67	4.52	61	0.24	-3.02*	30	4.93**	3.90*	292	-1.04	-1.40	451	-0.14	0.43
		(0.81)	*(1.17)*		*(0.83)*	*(1.22)*		*(-0.57)*	*(-1.94)*		*(2.26)*	*(1.87)*		*(-1.29)*	*(-1.41)*		*(-0.47)*	*(0.67)*
Deputy	10			15			4			8			135	0.12	-1.04	172	0.11	-2.41
														(-0.15)	*(-1.27)*		*(0.17)*	*(-0.73)*
Other	152	-0.23	-0.77	195	1.69**	0.39	205	-0.76	-1.95**	78	4.17***	4.94**	718	0.64	0.57	1,348	0.69	0.03
		(-1.35)	*(-0.92)*		*(2.51)*	*(0.87)*		*(-0.84)*	*(-2.07)*		*(3.55)*	*(2.52)*		*(0.43)*	*(0.23)*		*(0.78)*	*(0.03)*
Through a Company	16			194	1.50***	2.20***	276	1.34***	1.86***	62	6.12***	6.68***	786	0.57	2.15	1,334	1.07	2.23***
					(3.18)	*(3.14)*		*(3.35)*	*(3.63)*		*(6.46)*	*(5.83)*		*(-0.42)*	*(1.48)*		*(1.39)*	*(5.13)*
Household Member	70	1.21	2.99	187	2.53**	4.80***	123	-0.25	1.04	14			282	-0.92	-0.37	676	0.43	3.79**
		(0.50)	*(0.77)*		*(2.17)*	*(2.61)*		*(-0.62)*	*(0.82)*					*(-1.64)*	*(-0.54)*		*(-0.14)*	*(2.31)*
Other Insiders	46	1.26	2.25	33	1.23	4.91**	26	4.06*	4.67	2			63	1.63	4.92**	170	1.99**	3.91***
		(1.18)	*(0.87)*		*(0.36)*	*(2.27)*		*(1.94)*	*(1.53)*					*(0.86)*	*(2.12)*		*(2.15)*	*(3.13)*
ALL	837	0.45	0.68	1,250	1.61***	2.84***	1,093	1.15***	0.47**	328	4.62***	5.43***	3,988	-0.50	0.24			
		(0.93)	*(0.63)*		*(3.88)*	*(4.21)*		*(3.27)*	*(2.31)*		*(6.55)*	*(6.50)*		*(-1.02)*	*(-0.14)*			

For the OTHERS category we also estimate low and insignificant net CARs (-0.50% equal-weight, 0.24% €-volume-weight). This result, while similar to that of the DAX, is different due to one reason – the much higher mean bid-ask spread of 2.65%. Without taking bid-ask spreads into account, the CAR of this group is 2.15% (-0.50+2.65%, equal-weight). Here 57.8% of the gross CARs are positive, but only 47.5% of the net CARs. This shows that insiders of stocks in the OTHERS category, on average, can predict future stock price changes to some extent and that they use their informational advantage. However, the bid-ask spread diminishes abnormal profits completely.

Transactions by insiders of MDAX, SDAX, and TecDAX stocks are followed by statistically and economically significant abnormal performances. Most notably is the performance for the TecDAX where insiders earn 5.43% net of the bid-ask spread (t_G = 6.50) when weighting by transaction volume. More than 70% of the 328 individual CARs are positive, which shows that the group mean is not only related to a few influential observations (see Table A. 3 of Appendix C). Next in line are MDAX insiders, whose net CAR is 1.61% (equal-weight) or 2.84% (€-volume-weight). Here close to 60% of the net CARs are positive. For purchases by SDAX insiders we estimate 1.15% or 0.47%. Again close to 60% of the CARs are positive.

For MDAX, SDAX, and TecDAX stocks the transaction costs are higher than for DAX stocks (see Table 1). Adding the mean bid-ask spread to the net CARs results in gross CARs of 2.00%, 2.00%, and 6.49%. Thus MDAX and SDAX insiders seem to have an informational advantage that is similar to the OTHERS category. For TecDAX stocks the informational advantage is considerably higher than for all other groups of stocks.

7.2 Index and Insider Type Specific Abnormal Returns

When analyzing the different insider types across all indices ("ALL" in the last column of Table 5), we find evidence that supports Seyhun's (1986) informational hierarchy hypothesis. Overall, the €-volume-weight net CAR for CEOs is 1.88% and statistically significant (t_G = 3.38), while the CARs for the other members of the executive or supervisory board are all economically and statistically insignificant.

Our overall results for the insider types *Household Member*, *Through Company*, and *Other Insiders* show economically (3.79%, 2.23%, and 3.91%) and statistically significant €-volume-weight net CARs. The result for the group *Household Member*, typically consisting of trades made by (or in the name of) children or partners of insiders, support the study by Berkman/Koch/Westerholm (2014) who find that insiders channel their most profitable trades through the accounts of their children. A large number of insider trades is classified as *Through a Company*, which refers to insider transactions made through a corporate body/affiliated company. Typically these firms are investment trusts operated by one or more insiders, often by families. Note that the group *Other Insiders* has the smallest amount of trades of only 170.

The unusual results for some subsets with only a few observations, e.g. CFOs of MDAX stocks (-2.09%, t_G = -0.69), are typically related to outliers. An observation with a large individual CAR and €-volume can significantly bias the group mean. For example, the large abnormal performance for supervisory board chairs of MDAX stocks (4.52%, $t_G = 1.22$) stems from two out of the 45 transactions in the group. The first has an individual CAR of 25.7% and the second has a CAR of 15.5%. Each accounts for 10% of the total €-volume within that group.[42] Without these two observations, the group mean (€-volume-weight) is only 0.44%. The GRANK-test statistic seems to be robust with respect to such outliers in most of the cases.

Most important, the index-specific CARs do not seem to be related to the index-specific insider structure. Within the group of DAX insiders, all insider types have insignificant CARs. Within the group of TecDAX insiders all insider types have equal-weight CARs which are higher than 4%. Within the OTHERS category nearly all insider types have insignificant CARs.

7.3 Cross-Sectional Regressions for DAX, MDAX, SDAX, and TecDAX Purchases

There are possibly other factors that drive our result of index-specific CARs. One may argue, e.g., that abnormal returns may be explained by the book-to-market ratio for which we do not control in our model of size/industry adjusted returns. To check the robustness of our results we perform OLS regressions with the net CAR (%) over twenty days post insider trading day as the dependent variable.[43] Consistent with the results presented in Table 5, we winsorize abnormal returns (that is, the residuals in event and estimation time, not the CARs) at the 2% and 98% levels.[44] In all regressions we include ten control variables: *Book-to-Market*, *PriorReturn*, *Freefloat*, *Employee-Family-Hold*, *Debt/Total Assets*, *€-vol/Size*, *FinancialCrisis*, *Delay*, *Multi-Trade, LargeTrade*. Some of these control variables have been used in prior studies, e.g. *Debt/Total Assets*. All are described in detail in Table A. 1 of Appendix A.

We exclude the transactions with stocks not included in one of the four selection indices, i.e., stocks of the OTHERS category, mainly because our preliminary analysis does not reveal economically and statistically significant abnormal profits for this group. We also found that including them in the cross-sectional regressions produces less homogeneous results across the regression models (results are not tabulated). Thus our results presented in Table 6 only include the transactions made with stocks listed in the DAX, MDAX, SDAX, and TecDAX.[45]

In the first two regressions I and II of Table 6 we only include the control variables. The two equations differ only by the additional inclusion of *log(size)* in equation II. The intercepts

[42] Note that the €-volumes within each group are winsorized at the 97.5% level (see also footnote 33). Without winsorizing the mean CAR would be even larger.

[43] In all regressions presented here, we use Cook's distance to identify influential observations. The threshold of one is never exceeded.

[44] We also estimate the regressions without winsorizing abnormal returns and winsorizing at the 5% and 95% levels. We alternatively winsorize the vector of individual CARs on three different levels (2/98%, 5/95%, and 10/90%). The results do not change considerably.

[45] The sample for the cross-sectional regressions is slightly smaller because of missing data for the control variables. We exclude all transactions where the insider type – index membership combination contains less than twenty observations.

of these two standard regressions represent the part of abnormal performance which cannot be explained by the right-hand variables. In the other regressions we either additionally include dummy variables for the index memberships (settings III and IV), for the different insider types (setting V), or dummies for both (VI to VIII). To avoid the dummy variable trap we choose to omit one or two dummy variables. In the settings III and IV, the purchases made by insiders of DAX stocks are the reference group (=intercept) for which we do not find significant abnormal profits in the preliminary analyses. In regression V, the intercept represents purchases by CEOs. Since we have two categorical variables (index membership and insider type) in regression VI, VII, and VIII, the intercept refers to purchases by CEOs of DAX stocks. The coefficients of the dummies for the different insider types and index memberships thus measure the difference to the reference group (=intercept).

The control variables that have explanatory power within all setups (I-VIII) are *Book-to-Market*, *Debt/Total Assets,* and *FinancialCrisis*. For *Book-to-Market*, the coefficient is always positive and highly statistically significant. This suggests larger abnormal returns for insider purchases involving high book-to-market (value) firms and less for low book-to-market (growth) firms. It also reveals that our normal return model (size/industry adjusted returns) does not capture book-to-market effects, which is as expected. We include *Debt/Total Assets* as a proxy for leverage to control for highly leveraged firms for which possibly different aspects apply. Similar to Betzer/Theissen (2009), we find the coefficients to be negative and highly significant, suggesting lower profits for insiders purchasing stocks of relatively higher leveraged firms. *FinancialCrisis* is a 0/1 variable, which equals zero if the trade took place between September 1, 2008 and February 28, 2009 (6 months). We find the coefficient for *FinancialCrisis* to be around -3.0% and highly statistically significant in all setups. It suggests that insider's returns after purchases were much less in the hot season of the financial crisis. This supports the view that for many insider purchases the motive may have been to increase public confidence in their company and/or the stock market in general, even at the cost of a loss.

The statistically and economically significant intercept of 1.65% in regression (I) indicates that the abnormal performance found in the preliminary analyses (see Table 4) cannot be (fully) explained by the control variables. The regressions II and III constitute a horse-race between index dummies and *log(size).* They are correlated, which is indicated by the large variance inflation factor (VIF) of 8.544 in regression IV where both the aforementioned index dummies and *log(size)* are included. Note that the VIF of equation IV is still below the threshold of ten suggested by Belsley/Kuh/Welsch (1980), but larger than the threshold of five suggested by Menard (1995).[46] The inclusion of *log(size)* in II increases the explanatory power of the model only minimally, the adjusted R^2 is practically the same as in regression I. The inclusion of the index dummies in regression III, on the other hand, increases the fit of the model, the adjusted R^2 increases from 3.1% to 3.9%. This result is as expected since we

[46] See also O'Brien (2007) for a recent discussion of rules of thumb for VIFs.

Table 6: OLS-Regressions for Purchases made with DAX, MDAX, SDAX, and TecDAX stocks

The left-hand variable is the CAR net of the bid-ask spread (CAR^{net}) over twenty trading days post insider trading day. Daily abnormal returns (residuals in event and estimation time) are winsorized at the 2% and 98% levels. Returns are adjusted by the return on a portfolio of ten stocks sharing the same size and industry as the event stock (size/industry, see Section 5.1). The right-hand variables are described in Table A. 1 of Appendix A. All continuous variables are centered/scaled (mean 0, sd 1). Test statistics are based on White heteroskedasticity-consistent standard errors. Asterisks ***, **, * equal a significance level of 1%, 5%, and 10%.
[+] The intercept in regression (I) and (II) is the amount of abnormal returns not explained by the control variables. The intercept equals in regression (III) and (IV): "DAX"; in (V): "CEO"; in (VI) to (VIII) "DAX-CEO".

Regression	**I**	**II**	**III**	**IV**	**V**	**VI**	**VII**	**VIII**
Intercept[+]	1.65***	1.63***	0.83*	0.19	1.87***	0.98	0.48	-0.28
	(6.65)	*(6.57)*	*(1.80)*	*(0.27)*	*(4.22)*	*(1.62)*	*(0.53)*	*(-0.27)*
Executive Board Members: CFO					-0.92	-1.23*	0.83	0.81
					(-1.25)	*(-1.67)*	*(0.58)*	*(0.57)*
Other					0.31	0.25	0.47	0.43
					(0.58)	*(0.46)*	*(0.49)*	*(0.44)*
Supervisory Board Members: Chair					-0.74	-0.90	-0.66	-0.58
					(-1.23)	*(-1.51)*	*(-0.61)*	*(-0.53)*
Other					-0.27	-0.58	-0.28	-0.16
					(-0.30)	*(-0.65)*	*(-0.17)*	*(-0.10)*
Through a Company					-0.39	-0.52	1.36	1.15
					(-0.64)	*(-0.87)*	*(0.85)*	*(0.71)*
Household Member					-0.98	-0.90	0.78	0.86
					(-1.40)	*(-1.27)*	*(0.45)*	*(0.50)*
Other Insiders					0.31	0.48	1.19	1.31
					(0.35)	*(0.53)*	*(0.99)*	*(1.09)*
MDAX			0.90*	1.55**		1.12**	0.87	1.63
			(1.77)	*(2.12)*		*(2.14)*	*(0.76)*	*(1.29)*
SDAX			0.44	1.47		0.74	2.43**	3.73**
			(0.72)	*(1.43)*		*(1.19)*	*(2.05)*	*(2.56)*
TecDAX			3.64***	4.67***		3.98***	3.77**	5.05***
			(5.08)	*(4.24)*		*(5.52)*	*(2.39)*	*(2.72)*
log(size)		-0.28		0.59	-0.40			0.70
		(-1.01)		*(1.23)*	*(-1.43)*			*(1.41)*
Book-to-Market	1.15***	1.09***	1.14***	1.24***	1.03**	1.11***	1.05**	1.16***
	(2.80)	*(2.62)*	*(2.77)*	*(2.91)*	*(2.43)*	*(2.61)*	*(2.43)*	*(2.61)*
PriorReturn	0.17	0.17	0.10	0.13	0.21	0.14	0.16	0.20
	(0.48)	*(0.49)*	*(0.28)*	*(0.37)*	*(0.58)*	*(0.38)*	*(0.43)*	*(0.55)*
Freefloat	0.21	0.21	0.11	0.18	0.15	0.06	0.02	0.09
	(1.01)	*(1.01)*	*(0.52)*	*(0.82)*	*(0.71)*	*(0.28)*	*(0.08)*	*(0.41)*
Employee-Family-Hold	0.32	0.30	0.31	0.33	0.31	0.31	0.26	0.28
	(1.49)	*(1.39)*	*(1.44)*	*(1.55)*	*(1.43)*	*(1.43)*	*(1.16)*	*(1.27)*
Debt/Total Assets	-0.98***	-0.97***	-0.71***	-0.71***	-0.98***	-0.72***	-0.75***	-0.76***
	(-5.41)	*(-5.34)*	*(-3.82)*	*(-3.83)*	*(-5.35)*	*(-3.84)*	*(-3.94)*	*(-3.96)*
€-vol/Size	0.40**	0.17	0.01	0.21	0.11	-0.02	-0.02	0.22
	(2.05)	*(0.59)*	*(0.05)*	*(0.71)*	*(0.37)*	*(-0.07)*	*(-0.08)*	*(0.70)*
FinancialCrisis	-3.16***	-3.15***	-3.06***	-3.08***	-3.17***	-3.09***	-3.03***	-3.06***
	(-4.72)	*(-4.71)*	*(-4.60)*	*(-4.62)*	*(-4.74)*	*(-4.64)*	*(-4.55)*	*(-4.58)*
Delay	-0.01	-0.02	-0.03	-0.02	-0.01	-0.02	-0.02	-0.01
	(-0.20)	*(-0.29)*	*(-0.44)*	*(-0.29)*	*(-0.12)*	*(-0.26)*	*(-0.31)*	*(-0.15)*
Multi-Trade	0.04	0.05	0.09	0.07	0.07	0.08	0.19	0.17
	(0.09)	*(0.12)*	*(0.21)*	*(0.16)*	*(0.16)*	*(0.17)*	*(0.40)*	*(0.36)*
LargeTrade	0.77	1.19	1.26*	0.91	1.46**	1.46**	1.31*	0.90
	(1.23)	*(1.64)*	*(1.84)*	*(1.27)*	*(2.00)*	*(2.12)*	*(1.90)*	*(1.24)*
Interaction Terms *Index*Insider Type*	NO	NO	NO	NO	NO	NO	YES	YES
VIF (max)	3.305	3.425	3.324	8.544	3.619	3.385	16.923	19.395
N	3,162	3,162	3,162	3,162	3,162	3,162	3,162	3,162
F-test	11.237	10.309	10.997	10.329	6.757	7.652	4.833	4.765
Adj. R^2	3.137%	3.138%	3.949%	3.968%	3.174%	4.039%	4.405%	4.439%
R^2	3.443%	3.475%	4.344%	4.393%	3.726%	4.646%	5.554%	5.618%

assume linearity in *log(size)* in equation II. Based on our preliminary results - small or no abnormal performance in the very largest (DAX) and smallest (OTHERS) stocks and high CARs in the stocks with a market capitalization in between these two groups - the relationship is non-linear, it has an inverse U-shape.

Regression (V) includes 0/1 variables for the several insider types and also *log(size)* but no index dummies. The intercept represents the trades by CEOs. The coefficients of the other insider dummies thus measure whether their CARs are different. None of the coefficients for the insider dummies are statistically different from the intercept (=CEO). Thus we cannot support the informational hierarchy hypothesis, which is contrary to the result presented in the discussion of Table 5. The control variables seem to pick up the differences in the CARs of the different insiders which exist in Table 5. Ultimately, with respect to the different insider types, our results are in line with those by Betzer/Theissen (2009) and Dickgiesser/Kaserer (2010) for Germany. But different to the U.S., where Wang/Shin/Francis (2012) and Knewtson/Nofsinger (2013) find that CFO trades reveal more informational content than CEOs.

Regression (VI) includes both categorical variables, index membership and insider type, but not *log(size)*. We set the reference group (=intercept) to purchases by DAX-CEOs. However, there are reasons to believe that interaction effects exist. For example, transactions by a specific type of DAX insiders may not be comparable to those of their TecDAX counterparts. Also, CEO transactions of MDAX insiders are perhaps different to those of DAX-CEOs. For these reasons we perform the regressions (VII) and (VIII), containing the interaction terms between the 0/1 variables of index membership and insider type.[47] Thus the stand-alone 0/1 variables for the index membership and insider type in (VII) and (VIII) measure their pure effect.

Purchases by MDAX insiders are now similar to those by DAX insiders since the MDAX coefficient is insignificant, although positive. On the other hand, the pure abnormal performance earned by SDAX insiders is different to those by DAX insiders (3.73, *t*-statistic 2.42). Nevertheless, for both MDAX and SDAX trades, the results of equation VII and VIII differ from regression (VI). However, the results for the TecDAX are still large. Independent of the model applied, the coefficient remains positive and highly statistically significant for the TecDAX. This suggests that the high CARs in the TecDAX cannot be attributed to control variables and they are very different from the other insiders. Since TecDAX purchases exhibit large and robust CARs, we deepen our analysis in these trades in the next section.

[47] To test whether the inclusion of the interaction terms significantly adds to the explanatory power of the model, we conduct an incremental *F*-test, testing whether the R^2 of the unconstrained model (with interaction terms) significantly differs from the R^2 of the constrained model (no interaction terms). We can reject the null hypothesis of no interaction effects since F=1.668, which is larger than 1.607, the critical value at a 5% significance level.

8. Decomposing the TecDAX

8.1 Cross-Sectional Regression for only the TecDAX Trades

First we run regression (II) only for the purchases by insiders of TecDAX firms to allow that the coefficients of the control variables are different for the indices, which might especially be true for the Tec(nology)DAX. The OLS regression leads to the following result (t-statistics below are based on White heteroskedasticity-consistent standard errors):[48]

$$\begin{aligned} CAR^{net}(0,20) = {} & \underset{(5.94)}{5.13} + \underset{(1.86)}{1.82} log(size) + \underset{(0.17)}{0.27} Book\text{-}to\text{-}Market + \underset{(3.17)}{3.79} PriorReturn - \underset{(-0.33)}{0.21} Freefloat \\ & + \underset{(0.94)}{0.64} Employee\text{-}Family\text{-}Hold - \underset{(-1.47)}{1.18} Debt/Total\ Assets - \underset{(-0.88)}{0.66} €\text{-}vol/Size \\ & - \underset{(-2.04)}{3.24} FinancialCrisis - \underset{(-0.49)}{0.12} Delay + \underset{(1.86)}{2.60} Multi\text{-}Trade + \underset{(0.88)}{2.17} LargeTrade \end{aligned}$$

Adj. R^2=5.528%, N=295[49]

Indeed, we find the coefficients of some control variables different to those in regressions III to VIII in the overall analyses. Most importantly, the coefficient for *PriorReturn* is positive and highly significant (it is slightly positive and insignificant in the combined regression, see above). The coefficients of *Book-to-Market*, as well as *Debt/Total Assets* also differ, both are now insignificant. The economically and statistically significant intercept of 5.13% reveals that abnormal profits cannot be explained by the control variables, even if we allow for index-specific coefficients.

8.2 Clustering and Model Choice

The sample of TecDAX purchases consists of only 328 observations and the results thus could be biased by a clustering in a certain industry, stock, and/or time period. The TecDAX sample contains a selection of six different industries of which none are overrepresented. When decomposing them into sectors, we have 16 different subsectors of which the subsector "Renewable Energy Equipment" is slightly overrepresented (N=90), but does not stand out from the other subsectors according to its equal-weight net CAR of 4.81% (t_G = 5.03) and its €-volume-weight net CAR of 5.85% (t_G = 5.23). However, we find that trades by corporate insiders of Nordex SE (N=61), Kontron AG (N=43), and IDS Scheer AG (N=38) make up 43% of all TecDAX purchases, but the individual CARs of these trades are well distributed in both tails. Thus, a clustering of insider purchases within single stocks does not serve as an explanation. However, we find a clustering of trades in 2008 (N=92),[50] but the equal-weight net CAR (5.09%, t_G = 4.40) and the €-volume-weight net CAR (6.97%, t_G = 3.62) are in line with the overall result.

48 For completeness, Appendix D also includes the separate regressions for the DAX, MDAX, and SDAX. The separate index regressions for sales can be found in Appendix H.

49 The number of observations is slightly smaller than in Table 5 due to insufficient data for the cross-sectional regression.

50 2003: 20, 2004: 6, 2005: 27, 2006: 23, 2007: 35, 2008: 92, 2009: 26, 2010: 49, 2011: 44, and 2012: 17.

Abnormal returns could also be related to model choice. The equal-weight CARs net of the bid-ask spread for the TecDAX purchases are all very similar among the alternative models applied in this study. They are all highly statistically significant and range from 3.65% to 5.73% (equal-weight) and from 4.74% to 5.72% (€-volume-weight), respectively (results are not tabulated).

8.3 Technology Effect

One reason for the large abnormal returns associated with purchases by TecDAX insiders could be that insider trades with technology stocks generally transport a larger amount of unknown information to the stock exchange. Insider trades with (opaque) technology stocks may create larger changes in outsiders' expectations as companies in these sectors may be difficult to value. This points to higher informational asymmetries between corporate insiders and outsiders.[51] This is also mentioned by Betzer/Theissen (2010) for the stocks formally listed in the Neuer Markt. In this case, abnormal returns should be significantly higher compared to abnormal returns followed by non-technology based stocks.

To test this hypothesis we run OLS regressions with 0/1 variables, one for TecDAX membership and one for stocks which are not considered to be a technology stock (*NoTecStock*).[52] We additionally use the same control variables as in Table 6. Included in these regressions are all purchases and those in the OTHERS category. The results can be found in Table 7. Columns two to four show the results where the gross CAR (before transaction costs to neglect the impact of bid-ask spreads) is the left-hand variable, in columns five to seven the net CAR is the left-hand variable.

The first regression of Table 7 indicates that the null hypothesis of equal CARs for technology and non-technology stocks cannot be rejected because the coefficient for the 0/1 variable *NoTecStock* is insignificant. For the index membership in the TecDAX (regression II) we find the known result of larger CARs. In regression III, in which both dummy variables are included, the variable *NoTecStock* is insignificant. This suggests that the high abnormal returns for technology stocks implied by equation I is mainly related to the stocks with a TecDAX membership, which by definition only includes technology stocks. The same result holds for the CARs net of the bid-ask spread. Thus, we cannot find a statistically significant 'technology effect' in abnormal returns.[53] This is also supported by Dardas/Güttler (2011), who did not find an industry effect in their European insider trading study for the German stock market.

[51] This may highlight a regulatory oversight. The U.S. study by Gu/Li (2012) points to the fact that the SEC has widened their efforts in investigating insider trading of technology firms.

[52] A stock is considered to be a technology stock if it operates in the sectors Internet, computer services, software, biotechnology, medical equipment, alternative energy, advanced industrial equipment such as semiconductors, high technology communication products, and electronic and electrical equipment.

[53] Also note that the sub-sample of 1,787 insider purchases (including OTHERS) of stocks of technology firms, excluding the TecDAX, results in an equal-weight net CAR of -0.18% (t_G = -0.76) or a €-volume-weight net CAR of 0.78% (t_G = 0.63).

Table 7: OLS-Regressions for Purchases – Technology Stocks

Included in the regressions are all purchases by insiders of DAX, MDAX, SDAX, TecDAX, and OTHERS category. The left-hand variable is the CAR gross (CAR^{gross}) or net (CAR^{net}) of bid-ask spread over twenty trading days post insider trading day. Daily abnormal returns (residuals in event and estimation time) are winsorized at the 2% and 98% levels. Returns are adjusted by the return on a portfolio of ten stocks sharing the same size and industry as the event stock (size/industry, see Section 5.1). The right-hand variables are described in Table A. 1 of Appendix A. All continuous variables are centered/scaled (mean 0, sd 1). Test statistics are based on White heteroskedasticity-consistent standard errors. Asterisks ***, **, * equal a significance level of 1%, 5%, and 10%.

		CAR^{gross}			CAR^{net}	
Regression	I	II	III	I	II	III
Intercept	2.34*** *(7.80)*	1.97*** *(10.61)*	1.72*** *(5.27)*	1.23*** *(4.06)*	0.51*** *(2.74)*	0.52* *(1.58)*
TecDAX		3.50*** *(6.51)*	3.72*** *(6.22)*		4.24*** *(7.87)*	4.24*** *(7.13)*
NoTecStock	-0.30 *(-0.98)*		0.33 *(0.97)*	-0.73** *(-2.30)*		-0.01 *(-0.02)*
Included Control Variables: *log(size), Book-to-Market, PriorReturn, Freefloat, Employee-Family-Hold, Debt/Total Assets, €-vol/Size, FinancialCrisis, Delay, Multi-Trade, LargeTrade.*						
VIF (max)	3.565	3.562	3.566	3.565	3.562	3.566
N	6,784	6,784	6,784	6,784	6,784	6,784
F-test	6.082	8.865	8.265	10.123	13.768	12.707
Adj. R^2	0.891%	1.372%	1.373%	1.588%	2.209%	2.195%
R^2	1.066%	1.547%	1.562%	1.763%	2.382%	2.382%

8.4 The Effect of TecDAX Membership

The presented results suggest that an index related effect exists; i.e., a specific index membership, such as the TecDAX generates higher investor attention. To test this hypothesis, we look at insider purchases that did not have a TecDAX listing on its trading day, but were listed before or after this time point in the TecDAX. For the 250 observations that fulfills this condition (including OTHERS), we calculate an equal-weight net CAR of 1.20% (t_G = 0.08), and an €-volume-weight net CAR of 2.72% (t_G = 1.52). We combine the regular sample of trades with TecDAX stocks (N=328) and the trades with "earlier OR later TecDAX stocks" (N=250) to perform an OLS regression with a 0/1 variable, *EarlierOrLaterTecDAX*, for the purchases that do not have a TecDAX membership at the day of trade, but earlier or later in stock history. We obtain the following results (*t*- statistics below are based on White heteroskedasticity-consistent standard errors):

$$\begin{aligned}
CAR^{net}(0,20) = \; & \underset{(5.24)}{4.27} + \underset{(1.42)}{1.04}\,log(size) + \underset{(0.42)}{0.50}\,Book\text{-}to\text{-}Market + \underset{(2.67)}{2.56}\,PriorReturn - \underset{(-0.04)}{0.02}\,Freefloat \\
& - \underset{(-0.94)}{0.52}\,Employee\text{-}Family\text{-}Hold - \underset{(-2.90)}{2.02}\,Debt/Total\ Assets + \underset{(0.13)}{0.08}\,€\text{-}vol/Size \\
& - \underset{(-0.69)}{1.12}\,FinancialCrisis - \underset{(-0.08)}{0.02}\,Delay + \underset{(1.22)}{1.49}\,Multi\text{-}Trade + \underset{(1.29)}{3.11}\,LargeTrade \\
& \boldsymbol{- \underset{(-0.99)}{1.11}\,EarlierOrLaterTecDAX}
\end{aligned}$$

Adj. R^2=7.628%, N=511[54]

The coefficient for *EarlierOrLaterTecDAX* is negative as expected and suggests that a stock's CAR following insider purchases is lower before or after a TecDAX membership. Insiders of stocks with a former or later TecDAX membership earn about 1% less than those insiders of stocks that have a TecDAX membership. However, since the coefficient is statistically insignificant it limits our conclusions.

8.5 Summary of TecDAX results

Overall, the high abnormal returns after purchases by TecDAX insiders seem to be robust and thus indicate that insiders of TecDAX firms, as well as their imitators, earn abnormal profits from their stock market purchases. However, a note of caution is the small number of observations we have for these insiders. There are about three hundred observations, which is much lower when compared to the other indices and a larger sample may be preferable for a deeper analysis and stronger conclusions. It may also be useful to look at other stock markets with similar indices and/or segments to confirm our results.

Whether the high and significant abnormal returns (1) stem from real insider information that is transferred to the market or rather (2) from an overreaction of outside investors is, however, unclear.[55] Only a long-run performance study should reveal the answer since abnormal returns in (2) would disappear in the following months as stock prices revert back to "normal" since the value of the firm has not changed.

9. Summary and Conclusion

In this paper we calculate CARs in the twenty days following insider transactions. Unlike most prior German studies, we take bid-ask spreads into account to answer our main question: Do insiders and their imitators trade profitably?

We first confirm the results of prior studies on German insider transactions, but we find when incorporating the bid-ask spread, CARs over twenty days post insider trading day decrease or even disappear. For purchases, the abnormal performance in our baseline results are 2.69% gross and 1.26% net of bid-ask spread, both highly statistically significant. After we

[54] The number of observations is slightly smaller than the combined sample of 328+250=578 observations due to insufficient data for the cross-sectional regression.

[55] This is referring to the overreaction hypothesis discussed by Rozeff/Zaman (1998).

winsorize abnormal returns, the equal-weight net CAR is close to zero and statistically insignificant. However, the €-volume-weight performance net of bid-ask spread over all purchases remains economically and statistically significant and is also robust to winsorizing. For sales, we find -1.26% gross (highly statistically significant) and 0.03% net (statistically insignificant). When weighting the net CARs by €-volume and/or after winsorizing, the overall performance remains close to zero and statistically insignificant. Therefore, we conclude insiders and their imitators, on average, do not profit from their sales.

When we further analyze the purchase sample based on index membership, we find that DAX insiders earn small (0.45%) and statically insignificant returns. Conversely, insiders of TecDAX stocks on average earn large abnormal returns (4.62%), which are highly statistically significant and survive a number of robustness checks. We show that the large abnormal returns found for the TecDAX is not a general technology/industry related effect, but rather an index effect. Smaller in magnitude, but also robust are the results for purchases by SDAX insiders. The stocks not included in the selection indices have large CARs when transaction costs are not taken into account. Due to the large bid-ask spreads in this group of stocks, the CARs are close to zero and statistically insignificant when they are taken into account.

We also find that insider transactions are reported with a very short delay of about two days. This is why our results for insiders typically also hold for imitators of insider transactions. When examining returns based on our nine different insider types, we find contrary to U.S. studies no evidence that the insider types possess significantly different magnitudes of abnormal performance.

The German capital market seems to be very efficient if concentrating only on the top market index. The large and robust abnormal returns after insider purchases for the TecDAX and SDAX may reveal some regulatory oversight. But it is not clear whether short-run abnormal returns are related to outsiders' overreaction or *real* inside information. If abnormal returns persist in the long-run, this would give evidence that insiders do trade on inside information as their informational advantages become general knowledge in the long-run and should therefore be reflected in the stock price.

Appendix A: Variable Definitions

Table A. 1: Variable Definitions

Variable	Description
Insider Types	
Executive Board Members	
CEO	Chief Executive Officer
CFO	Chief Financial Officer
Other	All other executive board members (excluding CEO and CFO)
Supervisory Board Members	
Chair	Chairperson of the supervisory board (Aufsichtsratsvorsitzender)
Deputy	Deputy chairperson of the supervisory board (stellv. Aufsichtsratsvorsitzender)
Other	All other supervisory board members (excluding chairperson and deputy chairperson)
Through a Company	Insider transactions made through a corporate body/affiliated company. Typically, these firms are investment trusts operated by one or more (family) insider(s).
Household Member	Transactions from household members (living for more than one year in the household) of an insider who have a close relationship. These are typically trades by the children's or the partners of an insider.
Other Insiders	Other insider types, not listed above, such as other top managers with noticeable decision power and personally liable partner in a limited partnership that issues stocks.
Index Variables	
DAX	The DAX represents the 30 largest German based blue chips.
MDAX	The MDAX represents 50 'mid cap' stocks (size after the DAX).
SDAX	The SDAX contains 50 'small cap' stocks (size after the MDAX).
TecDAX	The 30 largest technology stocks below the DAX, usually seen as the follower of the NEMAX50, the former main index of the Neuer Markt. TecDAX trades are recorded from March 24, 2003 onwards (closing of the Neuer Markt, start of the TecDAX).
OTHERS	A self created category representing stocks that are not listed in the selection indices (DAX, MDAX, SDAX, TecDAX) but part of the top and middle segment of the FSE (up to 10/2007 Amtlicher and Geregelter Markt, afterwards Regulated Market.
Firm Specific Variables	
log(size)	The market value of equity of an insider transaction's underlying stock as a proxy for firm size. It is measured as of the end of the month before the month of trade (t-1), adjusted by inflation (source: Federal Statistical Office) in prices of December 2012.
Book-to-Market	Book value of equity divided by the market value of equity (size). We use the book value of equity as of December of the former year if the trade took place in the second half of a year. Insider trades made between January and June are based on the book value of equity as of December of two years before the trade. This is necessary as we want to make sure that the book value of equity was available at the time of trade. Numbers are winsorized at the 1% and the 99% levels to capture very large and negative values.
PriorReturn	The insider transaction underlying stock's prior return from t-12 to t-2 (11 month), excluding the current and last month. Numbers are winsorized at the 95% level to capture some very large values. (prior return can be at minimum -100%, but no maximum)
Freefloat	The percentage of equity that is publicly traded and available to ordinary investors.
Employee-Family-Hold	The percentage of equity (of >=5%) that is held by employees, "or by those with a substantial position in a company that provides significant voting power at an annual general meeting, (typically family members)." (quote from Datastream)
Debt/Total Assets	Total debt divided by total assets. Numbers are winsorized at the 95% level.
NoTecStock	This 0/1 variable equals one if the event stock is considered to be not a technology stock. Specifically, the firm does not operate in these sectors: Internet, computer services, software, biotechnology, medical equipment, alternative energy, advanced industrial equipment such as semiconductors, high technology communication products, and electronic and electrical equipment.

Table A. 1 continued.

Variable	**Description**
Trade Specific Variables	
Delay	The number of days elapsed from the trading to the announcement (exact stock market trading days of the FSE), maximal ten.
€-volume [€-vol]	Reported price multiplied by the number of stocks traded, adjusted by inflation in prices of December 2012.
€-vol/Size	The proportion of the market value of equity traded by the insider.
Multi Trade	This 0/1 variable equals one if another insider of the firm traded at the same day.
FinancialCrisis	This 0/1 variable equals one if a trade took place between September 1, 2008 and February 28, 2009 (6 months), the hot season of the financial crises.
LargeTrade	This 0/1 variable equals one if *€-volume* is larger than €500,000.

Appendix B: CARs for Insider Purchases and Sales: Full Sample – Alternative Models

Table A. 2: CARs for Insider Purchases and Sales: Full Sample – Alternative Models

This table shows CARs gross, $\overline{CAR}^{gross}$, and net, $\overline{CAR}^{net}$, of the bid-ask spread over twenty days post insider trading day and publication day (see Section 5.3). Each transaction's individual CAR is weighted (1) equal or (2) by transaction volume (€-vol, reported price multiplied by the number of stocks traded, adjusted by inflation in prices of December 2012). Transaction volumes are winsorized at 97.5%. The models used to calculate abnormal returns are explained in Section 5.1. For robustness checks, net CARs are also presented with daily abnormal returns (residuals in event and estimation time) winsorized on three different levels: "No" winsorizing at all, winsorizing in both tails at the 1% and 99% levels (1/99), and at 2% and 98% (2/98). Test statistics of the GRANK-test by Kolari/Pynnonen (2011) are given below in parentheses (variance is weighted accordingly for weighting procedure (2)). Asterisks ***, **, * equal a significance level of 1%, 5%, and 10%.

Abnormal Returns winsorized at	Purchases				Sales			
	Weighting: Equal		Weighting: €-vol		Weighting: Equal		Weighting: €-vol	
	$\overline{CAR}^{gross}$	$\overline{CAR}^{net}$	$\overline{CAR}^{gross}$	$\overline{CAR}^{net}$	$\overline{CAR}^{gross}$	$\overline{CAR}^{net}$	$\overline{CAR}^{gross}$	$\overline{CAR}^{net}$
Panel A: 20-Day Post Trading Day								
Raw Return (Purchases: N=7,630 Sales: N=4,061)								
No	2.88	1.23	2.48**	1.76	0.45	1.75	0.69	1.21
	(0.57)	(-0.17)	(1.98)	(1.37)	(-0.79)	(-0.23)	(0.15)	(0.65)
1/99	2.31	0.66	2.25	1.52	-0.18	1.12	0.75	1.27
	(0.26)	(-0.40)	(1.48)	(0.95)	(-0.92)	(-0.41)	(0.03)	(0.46)
2/99	2.01	0.36	2.06	1.33	-0.35	0.95	0.71	1.23
	(0.01)	(-0.56)	(0.92)	(0.48)	(-0.96)	(-0.52)	(-0.14)	(0.25)
Market with CDAX (Purchases: N=7,630 Sales: N=4,061)								
No	2.98***	1.32***	2.55***	1.82***	-0.85***	0.46	-0.48*	0.04
	(16.90)	(7.99)	(9.74)	(7.50)	(-5.54)	(0.33)	(-1.82)	(-0.56)
1/99	2.67***	1.02***	2.41***	1.69***	-1.44***	-0.14	-0.48**	0.04
	(7.52)	(2.90)	(7.78)	(5.81)	(-4.58)	(-1.22)	(-2.10)	(-0.83)
2/99	2.42***	0.77	2.33***	1.60***	-1.58***	-0.27	-0.54**	-0.02
	(3.22)	(0.75)	(4.64)	(3.27)	(-3.18)	(-1.28)	(-2.25)	(-1.12)
Market with Selection Index (Purchases: N=7,630 Sales: N=4,061)								
No	2.81***	1.16***	2.37***	1.64***	-0.95***	0.35	-0.41	0.11
	(17.61)	(8.17)	(9.99)	(7.69)	(-5.96)	(0.05)	(-1.52)	(-0.23)
1/99	2.47***	0.82***	2.28***	1.55***	-1.53***	-0.23	-0.40*	0.12
	(7.19)	(2.60)	(8.07)	(6.00)	(-4.89)	(-1.41)	(-1.69)	(-0.44)
2/99	2.23***	0.57	2.16***	1.44***	-1.64***	-0.33	-0.47**	0.05
	(3.02)	(0.58)	(4.65)	(3.25)	(-3.35)	(-1.38)	(-1.99)	(-0.84)
Characteristic Based Portfolio: Size/Prior Return (Purchases: N=7,213 Sales: N=3,898)								
No	2.61***	0.97***	2.42***	1.69***	-1.24***	0.07	-0.58*	-0.06
	(17.67)	(7.45)	(9.54)	(7.15)	(-6.15)	(-0.68)	(-1.78)	(-0.69)
1/99	2.25***	0.62**	2.41***	1.68***	-1.87***	-0.56**	-0.60**	-0.08
	(8.19)	(2.60)	(8.05)	(5.83)	(-5.43)	(-2.05)	(-1.98)	(-0.88)
2/99	1.96***	0.32	2.26***	1.53***	-2.03***	-0.72*	-0.68**	-0.16
	(3.24)	(0.39)	(5.06)	(3.44)	(-3.71)	(-1.82)	(-2.23)	(-1.22)
Characteristic Based Portfolio: Size/BM (Purchases: N=7,284 Sales: N=3,904)								
No	2.52***	0.88***	2.01***	1.30***	-1.38***	-0.09	-0.69**	-0.16
	(17.64)	(6.96)	(8.92)	(6.41)	(-6.19)	(-1.11)	(-2.28)	(-1.11)
1/99	2.13***	0.49*	1.94***	1.23***	-1.92***	-0.63**	-0.71**	-0.19
	(7.41)	(1.96)	(7.14)	(4.90)	(-5.40)	(-2.15)	(-2.49)	(-1.33)
2/99	1.86***	0.22	1.84***	1.12***	-2.08***	-0.79*	-0.79***	-0.27*
	(2.92)	(0.10)	(4.18)	(2.63)	(-3.72)	(-1.87)	(-2.80)	(-1.68)

Table A. 2 continued.

Abnormal Returns winsorized at	Purchases				Sales			
	Weighting: Equal		Weighting: €-vol		Weighting: Equal		Weighting: €-vol	
	$\overline{CAR}^{gross}$	$\overline{CAR}^{net}$	$\overline{CAR}^{gross}$	$\overline{CAR}^{net}$	$\overline{CAR}^{gross}$	$\overline{CAR}^{net}$	$\overline{CAR}^{gross}$	$\overline{CAR}^{net}$
Panel A: 20-Day Post Trading Day								
Market Model with CDAX (Purchases: N=7,630 Sales: N=4,061)								
No	2.86***	1.21***	2.87***	2.15***	-2.94***	-1.64***	-2.40***	-1.88***
	(14.98)	(6.60)	(10.09)	(7.85)	(-11.45)	(-6.06)	(-5.33)	(-4.01)
1/99	2.43***	0.78**	2.71***	1.98***	-3.50***	-2.20***	-2.29***	-1.78***
	(7.00)	(2.32)	(8.12)	(6.14)	(-8.54)	(-5.14)	(-5.67)	(-4.28)
2/99	2.11***	0.45	2.55***	1.83***	-3.59***	-2.28***	-2.30***	-1.78***
	(3.00)	(0.41)	(5.04)	(3.65)	(-5.37)	(-3.45)	(-5.52)	(-4.28)
Market Model with Selection Index (Purchases: N=7,630 Sales: N=4,061)								
No	2.60***	0.94***	2.57***	1.84***	-2.83***	-1.53***	-2.05***	-1.53***
	(15.01)	(6.18)	(10.15)	(7.86)	(-12.28)	(-6.55)	(-4.88)	(-3.52)
1/99	2.13***	0.48*	2.41***	1.69***	-3.40***	-2.10***	-1.99***	-1.47***
	(6.67)	(1.87)	(8.26)	(6.19)	(-8.84)	(-5.33)	(-5.16)	(-3.78)
2/99	1.80***	0.15	2.23***	1.51***	-3.50***	-2.19***	-2.04***	-1.52***
	(2.76)	(0.12)	(4.95)	(3.50)	(-5.49)	(-3.54)	(-5.16)	(-3.86)
Fama/French 3-Factor (Purchases: N=7,630 Sales: N=4,061)								
No	2.93***	1.27***	2.93***	2.21***	-3.07***	-1.76***	-2.34***	-1.82***
	(16.94)	(8.34)	(9.99)	(7.97)	(-12.34)	(-6.58)	(-5.25)	(-4.06)
1/99	2.54***	0.89***	2.87***	2.14***	-3.63***	-2.33***	-2.28***	-1.76***
	(7.79)	(3.14)	(8.29)	(6.46)	(-8.79)	(-5.35)	(-5.51)	(-4.28)
2/99	2.26***	0.60	2.75***	2.02***	-3.71***	-2.41***	-2.35***	-1.83***
	(3.41)	(0.85)	(5.14)	(3.86)	(-5.44)	(-3.52)	(-5.51)	(-4.36)
Carhardt 4-Factor (Purchases: N=7,630 Sales: N=4,061)								
No	2.91***	1.26***	3.09***	2.36***	-3.02***	-1.72***	-2.38***	-1.86***
	(16.74)	(8.37)	(10.20)	(8.17)	(-12.41)	(-6.76)	(-5.30)	(-4.10)
1/99	2.59***	0.94***	3.10***	2.38***	-3.64***	-2.33***	-2.34***	-1.82***
	(7.83)	(3.27)	(8.56)	(6.74)	(-8.87)	(-5.43)	(-5.61)	(-4.39)
2/99	2.29***	0.64	2.95***	2.22***	-3.73***	-2.43***	-2.41***	-1.89***
	(3.47)	(0.93)	(5.47)	(4.15)	(-5.47)	(-3.57)	(-5.70)	(-4.55)
Panel B: 20-Day Post Publication Day								
Raw Return (Purchases: N=7,230 Sales: N=3,793)								
No	2.53	0.91	2.07	1.36	0.50	1.78	0.45	0.95
	(0.38)	(-0.34)	(1.64)	(1.05)	(-0.81)	(-0.24)	(-0.25)	(0.27)
1/99	1.96	0.33	1.97	1.26	-0.18	1.10	0.53	1.03
	(0.11)	(-0.55)	(1.26)	(0.71)	(-0.95)	(-0.41)	(-0.32)	(0.15)
2/99	1.67	0.04	1.82	1.11	-0.36	0.92	0.49	0.99
	(-0.11)	(-0.68)	(0.75)	(0.31)	(-0.99)	(-0.52)	(-0.43)	(-0.01)
Market with CDAX (Purchases: N=7,230 Sales: N=3,793)								
No	2.42***	0.80***	1.77***	1.05***	-0.66***	0.63	-0.57*	-0.06
	(10.49)	(3.61)	(5.53)	(3.86)	(-3.98)	(0.44)	(-1.83)	(-0.75)
1/99	2.12***	0.50	1.75***	1.04***	-1.31***	-0.03	-0.55**	-0.04
	(5.44)	(1.17)	(4.76)	(3.15)	(-4.21)	(-1.03)	(-2.00)	(-0.93)
2/99	1.86**	0.24	1.70***	0.99*	-1.46***	-0.18	-0.60**	-0.10
	(2.27)	(-0.14)	(2.97)	(1.76)	(-3.16)	(-1.25)	(-2.19)	(-1.19)
Market with Selection Index (Purchases: N=7,230 Sales: N=3,793)								
No	2.18***	0.56***	1.41***	0.70***	-0.81***	0.48	-0.52*	-0.02
	(10.21)	(3.00)	(5.09)	(3.33)	(-4.55)	(0.06)	(-1.73)	(-0.60)
1/99	1.85***	0.22	1.44***	0.72***	-1.45***	-0.17	-0.50*	0.01
	(4.90)	(0.59)	(4.33)	(2.63)	(-4.72)	(-1.35)	(-1.86)	(-0.72)
2/99	1.60*	-0.02	1.35**	0.64	-1.56***	-0.28	-0.55**	-0.05
	(1.95)	(-0.46)	(2.58)	(1.31)	(-3.38)	(-1.40)	(-2.04)	(-1.00)

Table A. 2 continued.

Abnormal Returns winsorized at	Purchases				Sales			
	Weighting: Equal		Weighting: €-vol		Weighting: Equal		Weighting: €-vol	
	$\overline{CAR}^{gross}$	$\overline{CAR}^{net}$	$\overline{CAR}^{gross}$	$\overline{CAR}^{net}$	$\overline{CAR}^{gross}$	$\overline{CAR}^{net}$	$\overline{CAR}^{gross}$	$\overline{CAR}^{net}$
Panel B: 20-Day Post Publication Day								
Characteristic Based Portfolio: Size/Prior Return (Purchases: N=6,839 Sales: N=3,629)								
No	2.04***	0.42***	1.60***	0.88***	-1.04***	0.25	-1.02**	-0.51
	(10.62)	(3.07)	(5.42)	(3.61)	(-4.23)	(-0.06)	(-2.24)	(-1.24)
1/99	1.69***	0.07	1.68***	0.96***	-1.79***	-0.49*	-1.01**	-0.50
	(5.69)	(0.65)	(4.82)	(3.02)	(-4.81)	(-1.67)	(-2.40)	(-1.39)
2/99	1.39**	-0.23	1.54***	0.82*	-1.97***	-0.68*	-1.06**	-0.55
	(2.20)	(-0.56)	(3.20)	(1.74)	(-3.58)	(-1.69)	(-2.58)	(-1.64)
Characteristic Based Portfolio: Size/BM (Purchases: N=6,919 Sales: N=3,626)								
No	2.02***	0.38**	1.32***	0.62***	-1.07***	0.21	-0.84*	-0.32
	(10.35)	(2.54)	(5.18)	(3.33)	(-4.25)	(-0.07)	(-1.87)	(-0.79)
1/99	1.63***	-0.02	1.37***	0.67***	-1.73***	-0.45	-0.85**	-0.33
	(5.17)	(0.14)	(4.39)	(2.60)	(-4.61)	(-1.51)	(-2.00)	(-0.91)
2/99	1.34*	-0.31	1.28***	0.58	-1.92***	-0.63	-0.92**	-0.40
	(1.91)	(-0.85)	(2.73)	(1.33)	(-3.43)	(-1.58)	(-2.27)	(-1.22)
Market Model with CDAX (Purchases: N=7,230 Sales: N=3,793)								
No	2.37***	0.75***	2.10***	1.38***	-2.86***	-1.58***	-2.46***	-1.96***
	(9.59)	(3.10)	(5.51)	(3.81)	(-9.38)	(-5.17)	(-5.25)	(-4.13)
1/99	1.95***	0.33	2.04***	1.32***	-3.50***	-2.22***	-2.36***	-1.85***
	(5.07)	(0.80)	(4.66)	(3.05)	(-8.24)	(-5.04)	(-5.46)	(-4.27)
2/99	1.61**	-0.01	1.91***	1.20*	-3.60***	-2.32***	-2.35***	-1.85***
	(2.10)	(-0.40)	(3.01)	(1.75)	(-5.45)	(-3.57)	(-5.41)	(-4.29)
Market Model with Selection Index (Purchases: N=7,230 Sales: N=3,793)								
No	2.07***	0.45**	1.71***	1.00***	-2.75***	-1.47***	-2.14***	-1.63***
	(9.26)	(2.39)	(5.19)	(3.43)	(-9.77)	(-5.32)	(-4.53)	(-3.35)
1/99	1.61***	-0.02	1.66***	0.95***	-3.40***	-2.12***	-2.07***	-1.56***
	(4.65)	(0.22)	(4.40)	(2.72)	(-8.49)	(-5.14)	(-4.72)	(-3.49)
2/99	1.27*	-0.35	1.52***	0.81	-3.51***	-2.23***	-2.09***	-1.59***
	(1.81)	(-0.75)	(2.77)	(1.45)	(-5.54)	(-3.60)	(-4.82)	(-3.67)
Fama/French 3-Factor (Purchases: N=7,230 Sales: N=3,793)								
No	2.30***	0.68***	2.15***	1.43***	-2.90***	-1.62***	-2.36***	-1.86***
	(10.88)	(4.01)	(5.96)	(4.39)	(-9.32)	(-4.91)	(-5.05)	(-3.93)
1/99	1.92***	0.30	2.18***	1.47***	-3.53***	-2.25***	-2.28***	-1.78***
	(5.65)	(1.33)	(5.17)	(3.65)	(-8.15)	(-4.90)	(-5.26)	(-4.10)
2/99	1.63**	0.01	2.07***	1.36**	-3.64***	-2.36***	-2.34***	-1.84***
	(2.38)	(-0.11)	(3.31)	(2.13)	(-5.35)	(-3.46)	(-5.33)	(-4.24)
Carhardt 4-Factor (Purchases: N=7,230 Sales: N=3,793)								
No	2.25***	0.63***	2.18***	1.47***	-2.85***	-1.57***	-2.36***	-1.86***
	(10.64)	(3.91)	(5.86)	(4.26)	(-9.36)	(-4.99)	(-4.88)	(-3.80)
1/99	1.93***	0.31	2.29***	1.58***	-3.56***	-2.28***	-2.32***	-1.81***
	(5.61)	(1.33)	(5.10)	(3.58)	(-8.25)	(-5.00)	(-5.15)	(-4.01)
2/99	1.64**	0.01	2.16***	1.45**	-3.68***	-2.40***	-2.38***	-1.88***
	(2.39)	(-0.09)	(3.35)	(2.17)	(-5.43)	(-3.54)	(-5.34)	(-4.23)

Appendix C: Percentage of Positive CARs for Purchases and Sales Grouped by Insider Type and the Index Membership

Table A. 3: Percentage of Positive CARs for Insider Purchases and Sales Grouped by Insider Type and the Index Membership of the Event Stock

This table shows the percentage of CARs, gross and net of the bid-ask spread (see Table 4 or formula 1, Section 5.3) for insider purchases and sales over twenty days post insider trading day. The sample is grouped by the type of the insider and/or the event stock's index membership. Daily abnormal returns (residuals in event and estimation time) are winsorized at the 2% and 98% levels. Returns are adjusted by the return on a portfolio of ten stocks sharing the same size and industry as the event stock (size/industry, see Section 5.1).

	DAX			MDAX			SDAX			TecDAX			OTHERS			ALL		
	N	% of CAR^{gross} positive	% of CAR^{net} positive	N	% of CAR^{gross} positive	% of CAR^{net} positive	N	% of CAR^{gross} positive	% of CAR^{net} positive	N	% of CAR^{gross} positive	% of CAR^{net} positive	N	% of CAR^{gross} positive	% of CAR^{net} positive	N	% of CAR^{gross} positive	% of CAR^{net} positive
Panel A: PURCHASES																		
CEO	102	56.9	56.9	166	62.0	60.8	175	72.0	68.6	44	72.7	70.5	756	53.6	43.9	1,243	58.2	51.6
CFO	56	55.4	55.4	114	52.6	51.8	65	63.1	56.9	38	68.4	65.8	210	57.1	48.6	483	57.6	52.6
Executive B. Member	362	53.6	52.5	301	60.5	57.8	158	62.7	58.2	52	73.1	73.1	746	53.9	43.7	1,619	56.5	50.6
Supervisory B. Chair	23	52.2	47.8	45	57.8	55.6	61	49.2	49.2	30	76.7	73.3	292	56.5	46.9	451	56.8	49.9
Supervisory B. Deputy	10	60.0	60.0	15	60.0	60.0	4	50.0	50.0	8	75.0	75.0	135	62.2	45.2	172	62.2	48.8
Supervisory B. Member	152	42.8	42.1	195	59.5	57.9	205	49.3	44.4	78	69.2	66.7	718	64.1	52.6	1,348	59.1	51.8
Company	16	43.8	43.8	194	62.4	60.8	276	63.8	59.8	62	82.3	80.6	786	60.7	50.4	1,334	62.4	55.2
Household Member	70	47.1	47.1	187	59.4	58.8	123	45.5	43.9	14	64.3	42.9	282	53.5	44.7	676	53.3	48.7
Other Insiders	46	56.5	54.3	33	57.6	54.5	26	80.8	80.8	2	100.0	100.0	63	63.5	60.3	170	63.5	61.2
ALL	837	51.6	50.8	1,250	59.8	58.2	1,093	59.7	56.0	328	73.5	70.7	3,988	57.8	47.5	7,496	58.4	51.9
Panel B: SALES																		
CEO	20	55.0	60.0	67	41.8	41.8	36	47.2	50.0	43	39.5	41.9	175	34.3	38.3	341	39.0	41.9
CFO	10	0.0	0.0	49	30.6	32.7	31	51.6	54.8	55	30.9	30.9	60	48.3	56.7	205	37.6	41.0
Executive B. Member	140	54.3	54.3	158	31.6	34.8	115	41.7	46.1	144	33.3	36.1	376	44.9	50.3	933	41.9	45.6
Supervisory B. Chair	17	47.1	47.1	27	37.0	37.0	20	40.0	45.0	14	14.3	14.3	150	36.0	44.7	228	36.0	42.1
Supervisory B. Deputy	12	41.7	41.7	13	69.2	76.9	1	100.0	100.0	4	75.0	75.0	83	44.6	54.2	113	48.7	56.6
Supervisory B. Member	196	43.9	44.9	206	52.4	54.9	72	51.4	52.8	51	35.3	35.3	439	38.0	43.5	964	43.2	46.5
Company	5	40.0	40.0	60	43.3	45.0	44	50.0	52.3	64	53.1	53.1	181	33.7	45.3	354	41.0	47.5
Household Member	49	42.9	42.9	89	36.0	39.3	141	52.5	58.2	41	53.7	53.7	345	46.1	56.8	665	46.3	53.5
Other Insiders	117	52.1	53.0	34	29.4	29.4	22	50.0	50.0	0			46	47.8	63.0	219	47.5	51.1
ALL	566	47.7	48.4	703	41.0	43.2	482	48.5	52.3	416	38.7	39.9	1,855	40.9	48.5	4,022	42.5	47.1

Appendix D: Purchases - Trading Day: Index Specific Regressions

Table A. 4: Index Specific OLS-Regressions for Purchases

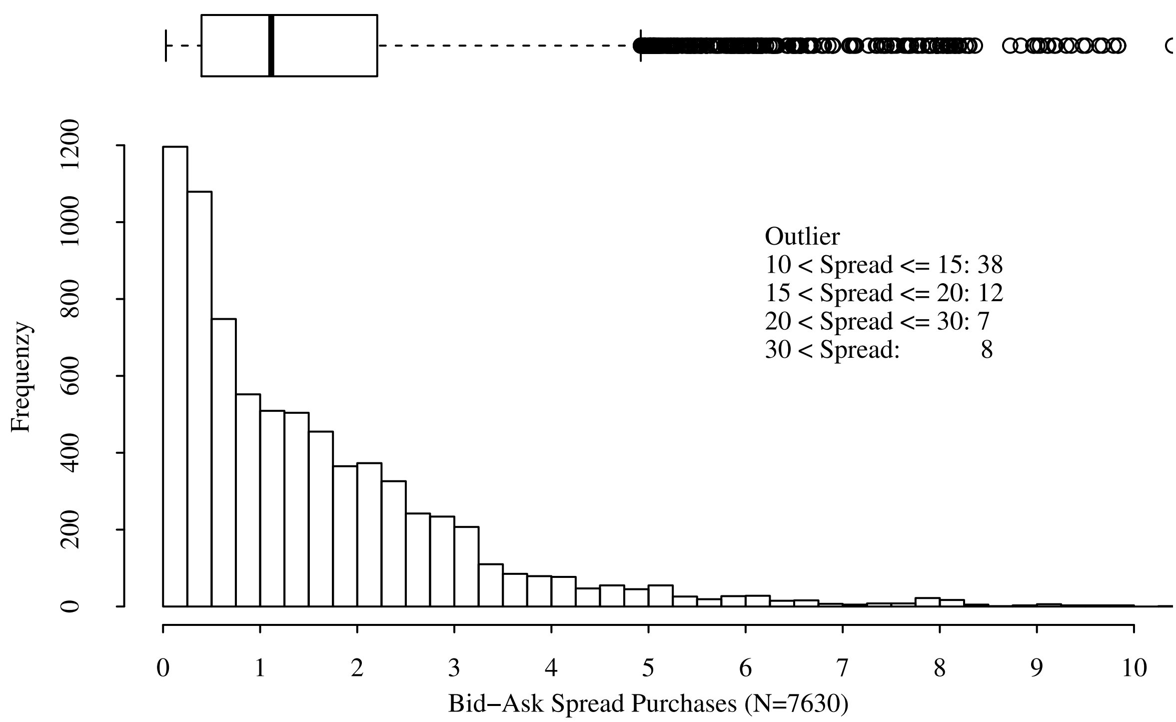
The left-hand variable is the CAR net of the bid-ask spread (CAR^{net}) over twenty trading days post insider trading day. Daily abnormal returns (residuals in event and estimation time) are winsorized at the 2% and 98% levels. Returns are adjusted by the return on a portfolio of ten stocks sharing the same size and industry as the event stock (size/industry, see Section 5.1). The right-hand variables are described in Table A. 1 of Appendix A. All continuous variables are centered/scaled (mean 0, sd 1). Test statistics are based on White heteroskedasticity-consistent standard errors. Asterisks ***, **, * equal a significance level of 1%, 5%, and 10%.

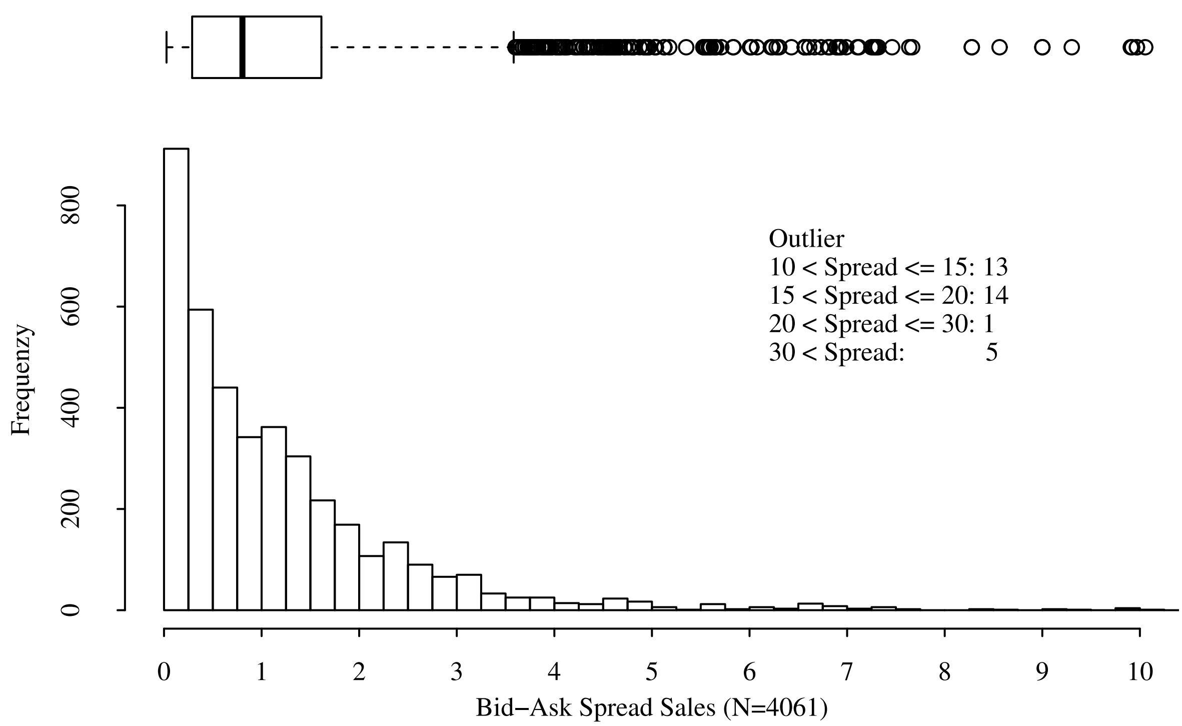
$^{+}$ The intercept in regression (I) is the amount of abnormal returns not explained by the control variables. In regressions (II) the intercept represents transactions by the CEO (all other insider types measure the difference).

Regression	**DAX**		**MDAX**		**SDAX**		**TecDAX**	
	I	**II**	**I**	**II**	**I**	**II**	**I**	**II**
Intercept^{+}	0.72	0.15	1.07**	0.99	2.25***	3.69***	5.13***	5.00***
	(1.55)	*(0.17)*	*(2.37)*	*(1.26)*	*(5.08)*	*(4.79)*	*(5.94)*	*(3.32)*
Executive Board Members: CFO		1.25		-2.36*		-0.83		-1.37
		(0.84)		*(-1.89)*		*(-0.57)*		*(-0.63)*
Other		0.59		1.01		-0.41		0.03
		(0.58)		*(1.04)*		*(-0.38)*		*(0.02)*
Supervisory Board Members: Chair		0.19		0.62		-3.36***		-0.36
		(0.17)		*(0.53)*		*(-3.09)*		*(-0.21)*
Other		0.21		0.64		-2.41		0.79
		(0.13)		*(0.42)*		*(-1.32)*		*(0.33)*
Through a Company				0.15		-2.08**		2.05
				(0.17)		*(-2.02)*		*(1.00)*
Household Member		1.23		-0.34		-3.07**		
		(0.70)		*(-0.31)*		*(-2.57)*		
Other Insiders		1.61		-1.21		1.58		
		(1.23)		*(-0.61)*		*(0.87)*		
log(size)	0.32	0.35	0.87*	0.78*	-0.11	0.09	1.82*	1.30
	(0.82)	*(0.83)*	*(1.95)*	*(1.76)*	*(-0.21)*	*(0.17)*	*(1.86)*	*(1.21)*
Book-to-Market	0.67	0.72	1.64*	1.50*	2.37***	2.18***	0.27	0.28
	(0.41)	*(0.44)*	*(1.87)*	*(1.70)*	*(3.71)*	*(3.23)*	*(0.17)*	*(0.18)*
PriorReturn	0.11	0.11	0.46	0.55	-1.62***	-1.51***	3.79***	3.64***
	(0.08)	*(0.07)*	*(0.63)*	*(0.74)*	*(-2.89)*	*(-2.58)*	*(3.17)*	*(3.01)*
Freefloat	0.16	0.16	1.14***	1.02***	-0.20	-0.47	-0.21	-0.32
	(0.42)	*(0.43)*	*(3.07)*	*(2.78)*	*(-0.47)*	*(-1.07)*	*(-0.33)*	*(-0.46)*
Employee-Family-Hold	-0.16	-0.14	1.21***	1.19***	-0.40	-0.61	0.64	0.48
	(-0.44)	*(-0.36)*	*(3.36)*	*(3.14)*	*(-1.09)*	*(-1.55)*	*(0.94)*	*(0.68)*
Debt/Total Assets	-0.41	-0.37	-0.86***	-0.87***	-0.97***	-0.94***	-1.18	-1.28
	(-1.16)	*(-1.04)*	*(-2.68)*	*(-2.66)*	*(-2.75)*	*(-2.61)*	*(-1.47)*	*(-1.49)*
€-vol/Size	0.83*	0.88*	0.04	0.02	0.00	0.14	-0.66	-1.27
	(1.86)	*(1.89)*	*(0.08)*	*(0.04)*	*(0.00)*	*(0.34)*	*(-0.88)*	*(-1.47)*
FinancialCrisis	-0.82	-0.83	-4.10***	-4.19***	-4.20***	-3.95***	-3.24**	-3.13*
	(-0.62)	*(-0.62)*	*(-3.16)*	*(-3.20)*	*(-3.75)*	*(-3.54)*	*(-2.04)*	*(-1.90)*
Delay	-0.13	-0.13	0.22*	0.20*	-0.25	-0.16	-0.12	-0.19
	(-0.95)	*(-0.96)*	*(1.91)*	*(1.76)*	*(-1.60)*	*(-0.99)*	*(-0.49)*	*(-0.71)*
Multi-Trade	0.75	0.65	-0.06	0.04	-1.25	-0.84	2.60*	2.72*
	(0.99)	*(0.84)*	*(-0.07)*	*(0.04)*	*(-1.25)*	*(-0.79)*	*(1.86)*	*(1.93)*
LargeTrade	-1.23	-1.20	2.03	2.18*	-0.50	-0.60	2.17	2.25
	(-0.94)	*(-0.89)*	*(1.62)*	*(1.72)*	*(-0.34)*	*(-0.41)*	*(0.88)*	*(0.92)*
VIF (max)	6.447	6.543	3.538	3.605	3.769	3.906	3.950	4.421
N	764	764	1,128	1,128	975	975	295	295
F-test	1.267	0.947	5.981	4.248	4.528	3.842	2.564	1.927
Adj. R^2	0.383%	-0.118%	4.637%	4.932%	3.831%	4.990%	5.528%	4.804%
R^2	1.819%	2.112%	5.567%	6.450%	4.917%	6.746%	9.063%	9.985%

Appendix E: Distribution of Bid-Ask Spreads

Figure A. 1: Distribution of Bid-Ask Spreads (%) for Purchases and Sales





Appendix F: List of Largest Transactions

Table A. 5: The Largest Transactions (€-volume) Included in the Final Sample

This table shows all insider transactions of the final sample larger than €10 mio. Note that many sizeable transactions are excluded during the sample selection process.

WKN	Company	Trans-action Type	Price	Number of Stocks Traded	€-volume (pure, not adjusted by inflation)	Day of Trans-actions	Index Member-ship at the Day of Trade
716460	SAP AG	S	172.82	1,460,000	252,317,200	02.03.2006	DAX
604700	HeidelbergCement AG	P	75.8	2,800,000	212,240,000	14.12.2005	MDAX
604700	HeidelbergCement AG	P	96	2,083,333	199,999,968	26.04.2006	MDAX
716460	SAP AG	S	134.13	745,546	100,000,085	14.12.2004	DAX
656990	MLP AG	S	15.75	5,000,000	78,750,000	09.12.2003	MDAX
604700	HeidelbergCement AG	P	67.79	440,306	29,848,344	21.10.2008	MDAX
627500	Arcandor AG	P	9.0175	3,030,000	27,323,025	11.05.2005	MDAX
A1YCMM	SolarWorld AG	S	105	249,500	26,197,500	04.05.2005	TecDAX
550135	Axel Springer AG	S	122	211,051	25,748,222	06.12.2006	OTHERS
627500	Arcandor AG	P	9.0152	2,105,716	18,983,451	10.05.2005	MDAX
716460	SAP AG	S	126.11	150,000	18,916,500	16.10.2003	DAX
716460	SAP AG	S	126.11	150,000	18,916,500	16.10.2003	DAX
716460	SAP AG	P	71.3	263,763	18,806,302	24.07.2002	DAX
604700	HeidelbergCement AG	P	65.656	281,730	18,497,265	22.10.2008	MDAX
A1KRCK	Conergy AG	S	54.74	300,000	16,422,000	30.03.2007	TecDAX
A1EWWW	adidas AG	S	155.396	100,000	15,539,600	03.08.2005	DAX
604700	HeidelbergCement AG	P	57.38	243,079	13,947,873	24.10.2008	MDAX
716460	SAP AG	S	123.57	109,903	13,580,714	31.10.2003	DAX
716460	SAP AG	S	123.57	109,903	13,580,714	31.10.2003	DAX
627500	Arcandor AG	P	9.8242	1,325,000	13,017,065	01.11.2005	MDAX
514000	Deutsche Bank AG	S	45.578	284,364	12,960,742	07.08.2009	DAX
627500	Arcandor AG	P	10.7228	1,169,856	12,544,132	21.09.2005	MDAX
PAT1AG	PATRIZIA Immobilien AG	P	8.28	1,509,000	12,494,520	01.11.2007	SDAX
577220	Fielmann AG	P	32.27	383,061	12,361,378	16.01.2003	MDAX
604843	Henkel AG & Co. KGaA	P	60.701	200,000	12,140,200	16.08.2012	DAX
604700	HeidelbergCement AG	P	61.551	196,166	12,074,213	23.10.2008	MDAX
604700	HeidelbergCement AG	P	38.2938	300,000	11,488,140	29.07.2011	DAX
716460	SAP AG	P	38.7071	292,069	11,305,144	15.08.2007	DAX
716460	SAP AG	S	172.5418	63,625	10,977,972	10.03.2006	DAX

Appendix G: Additional Results for Purchases - Publication Day

Table A. 6: Equal- and €-Volume-Weight CARs for Insider Purchases Grouped by Insider Type and the Index Membership of the Event Stock

This table shows CARs net of the bid-ask spread (see Table 4 or formula 1, Section 5.3) for insider purchases over twenty days post publication day. All observations with a delay of larger than ten days are excluded. The sample is grouped by the type of the insider and/or the event stock's index membership. Each transaction's individual net CAR is weighted (1) equal [1/N] or (2) by transaction volume (€-vol*), with outliers in volume winsorized at 97.5% for each group individually, see Section 5.4 for details. Daily abnormal returns (residuals in event and estimation time) are winsorized at the 2% and 98% levels. The €-volume is insider's transaction volume (reported price multiplied by the number of stocks traded, adjusted by inflation in prices of December 2012). Returns are adjusted by the return on a portfolio of ten stocks sharing the same size and industry as the event stock (size/industry, see Section 5.1). Test statistics of the GRANK-test by Kolari/Pynnonen (2011) are given below in parentheses (variance is weighted accordingly for weighting procedure (2)). Asterisks ***, **, * equal a significance level of 1%, 5%, and 10%.

	DAX			MDAX			SDAX			TecDAX			OTHERS			ALL		
	N	Equal	€-vol*	N	Equal	€-vol*	N	Equal	€-vol*	N	Equal	€-vol*	N	Equal	€-vol*	N	Equal	€-vol*
Executive Board Members																		
CEO	97	-0.16 *(0.52)*	0.08 *(0.62)*	147	-0.17 *(0.14)*	2.62* *(1.95)*	167	3.40*** *(4.16)*	4.27*** *(3.42)*	42	5.22*** *(2.88)*	3.30 *(0.92)*	710	-1.81** *(-2.00)*	-1.45 *(-1.51)*	1,163	-0.46 *(-0.42)*	0.97* *(1.91)*
CFO	53	-0.14 *(-0.02)*	-0.09 *(-0.19)*	108	-1.64 *(-0.78)*	-2.90 *(-1.35)*	63	2.04 *(1.24)*	0.46 *(0.03)*	35	3.48* *(1.97)*	3.13 *(1.22)*	199	0.01 *(-0.57)*	1.25 *(0.77)*	458	0.15 *(0.15)*	-0.52 *(-0.12)*
Other	342	-0.47 *(-0.40)*	0.05 *(0.35)*	289	0.83 *(0.96)*	0.54 *(0.92)*	156	2.09** *(2.23)*	-0.45 *(-0.68)*	51	3.79*** *(2.99)*	1.78 *(0.91)*	717	-2.11** *(-2.15)*	-1.08 *(-1.06)*	1,555	-0.59 *(-0.72)*	-0.01 *(0.28)*
Supervisory Board Members																		
Chair	21	0.59 *(0.99)*	1.12 *(1.41)*	44	0.70 *(0.73)*	3.70 *(0.96)*	58	0.11 *(-0.92)*	-2.28 *(-1.43)*	26	4.08 *(1.55)*	3.48 *(1.54)*	282	-2.40** *(-2.33)*	-3.17* *(-1.73)*	431	-1.21 *(-1.52)*	-0.03 *(0.29)*
Deputy	8			15			4			7			130	-0.19 *(-0.21)*	-0.84 *(-1.36)*	164	-0.10 *(0.12)*	-1.85 *(-0.97)*
Other	141	-0.66* *(-1.94)*	-1.30* *(-1.79)*	182	1.11 *(1.30)*	0.20 *(0.54)*	197	-1.21 *(-1.07)*	-1.29 *(-0.73)*	71	2.47** *(2.11)*	3.25* *(1.73)*	687	0.33 *(-0.08)*	0.14 *(-0.12)*	1,278	0.21 *(-0.07)*	-0.26 *(-0.54)*
Through a Company	16			178	0.42 *(0.87)*	0.82 *(0.88)*	267	1.24*** *(2.84)*	1.95*** *(3.16)*	62	2.94** *(2.14)*	3.54** *(2.39)*	751	-0.42 *(-1.16)*	0.62 *(0.05)*	1,274	0.14 *(0.11)*	1.03* *(1.90)*
Household Member	66	1.82 *(0.62)*	3.04 *(0.99)*	174	2.27* *(1.93)*	4.78* *(1.90)*	118	-1.06 *(-1.15)*	1.03 *(1.07)*	13			269	-2.07** *(-2.03)*	-0.91 *(-0.58)*	640	-0.26 *(-0.79)*	3.68* *(1.93)*
Other Insiders	39	0.74 *(0.03)*	2.63 *(-0.04)*	30	0.69 *(-0.26)*	4.00 *(1.20)*	25	4.74** *(2.35)*	5.21 *(1.44)*	2			60	0.11 *(0.24)*	3.65 *(1.54)*	156	1.34 *(1.06)*	3.47* *(1.81)*
ALL	783	-0.25 *(-0.72)*	0.01 *(-0.30)*	1,167	0.67 *(1.57)*	1.98** *(2.14)*	1,055	1.01** *(2.47)*	0.83** *(2.26)*	309	3.43*** *(4.39)*	3.32*** *(3.23)*	3,805	-1.08 *(-1.64)*	-0.58 *(-0.96)*			

Table A. 7: OLS-Regressions for Purchases made with DAX, MDAX, SDAX, and TecDAX stocks

The left-hand variable is the CAR net of the bid-ask spread (CAR^{net}) over twenty trading days post publication day. Daily abnormal returns (residuals in event and estimation time) are winsorized at the 2% and 98% levels. Returns are adjusted by the return on a portfolio of ten stocks sharing the same size and industry as the event stock (size/industry, see Section 5.1). The right-hand variables are described in Table A. 1 of Appendix A. All continuous variables are centered/scaled (mean 0, sd 1). Test statistics are based on White heteroskedasticity-consistent standard errors. Asterisks ***, **, * equal a significance level of 1%, 5%, and 10%.

[+] The intercept in regression (I) and (II) is the amount of abnormal returns not explained by the control variables. The intercept equals in regression (III) and (IV): "DAX"; in (V): "CEO"; in (VI) to (VIII) "DAX-CEO".

Regression	**I**	**II**	**III**	**IV**	**V**	**VI**	**VII**	**VIII**
Intercept[+]	1.12***	1.08***	0.32	0.61	1.81***	0.95	0.13	0.07
	(4.42)	*(4.26)*	*(0.67)*	*(0.79)*	*(3.80)*	*(1.49)*	*(0.14)*	*(0.06)*
Executive Board Members: CFO					-1.53*	-1.65**	0.16	0.16
					(-1.92)	*(-2.07)*	*(0.11)*	*(0.11)*
Other					-0.34	-0.36	0.15	0.14
					(-0.60)	*(-0.64)*	*(0.15)*	*(0.15)*
Supervisory Board Members: Chair					-1.34**	-1.38**	-0.74	-0.73
					(-2.12)	*(-2.19)*	*(-0.66)*	*(-0.65)*
Other					-0.88	-1.08	0.86	0.87
					(-0.87)	*(-1.07)*	*(0.52)*	*(0.53)*
Through a Company					-1.20*	-1.35**	-2.54	-2.56
					(-1.88)	*(-2.09)*	*(-1.43)*	*(-1.43)*
Household Member					-0.89	-0.74	2.46	2.47
					(-1.19)	*(-0.99)*	*(1.39)*	*(1.39)*
Other Insiders					0.29	0.45	1.00	1.01
					(0.31)	*(0.49)*	*(0.83)*	*(0.84)*
MDAX			0.49	0.20		0.62	-0.22	-0.16
			(0.92)	*(0.25)*		*(1.14)*	*(-0.18)*	*(-0.12)*
SDAX			1.06	0.60		1.26*	3.81***	3.91**
			(1.64)	*(0.53)*		*(1.91)*	*(3.03)*	*(2.46)*
TecDAX			2.54***	2.08*		2.87***	4.39***	4.50**
			(3.34)	*(1.69)*		*(3.73)*	*(2.58)*	*(2.22)*
log(size)		-0.64**		-0.26	-0.71**			0.06
		(-2.26)		*(-0.49)*	*(-2.46)*			*(0.10)*
Book-to-Market	1.11***	0.97**	1.07**	1.02**	0.90**	1.00**	0.88**	0.88*
	(2.65)	*(2.29)*	*(2.54)*	*(2.34)*	*(2.05)*	*(2.30)*	*(1.96)*	*(1.92)*
PriorReturn	0.30	0.31	0.30	0.29	0.34	0.34	0.41	0.42
	(0.84)	*(0.86)*	*(0.84)*	*(0.80)*	*(0.94)*	*(0.92)*	*(1.11)*	*(1.12)*
Freefloat	0.32	0.33	0.34	0.31	0.25	0.26	0.25	0.25
	(1.52)	*(1.55)*	*(1.52)*	*(1.40)*	*(1.16)*	*(1.16)*	*(1.05)*	*(1.08)*
Employee-Family-Hold	0.72***	0.67***	0.69***	0.68***	0.64***	0.64***	0.62***	0.62***
	(3.32)	*(3.10)*	*(3.17)*	*(3.15)*	*(2.91)*	*(2.92)*	*(2.73)*	*(2.75)*
Debt/Total Assets	-0.91***	-0.89***	-0.76***	-0.76***	-0.90***	-0.77***	-0.77***	-0.77***
	(-4.71)	*(-4.59)*	*(-3.80)*	*(-3.80)*	*(-4.60)*	*(-3.78)*	*(-3.74)*	*(-3.73)*
€-vol/Size	0.43**	-0.09	0.03	-0.05	-0.06	0.07	0.11	0.13
	(2.14)	*(-0.29)*	*(0.12)*	*(-0.18)*	*(-0.21)*	*(0.26)*	*(0.40)*	*(0.41)*
FinancialCrisis	-4.00***	-3.98***	-3.94***	-3.93***	-4.00***	-3.96***	-3.93***	-3.93***
	(-5.92)	*(-5.91)*	*(-5.87)*	*(-5.85)*	*(-5.93)*	*(-5.89)*	*(-5.84)*	*(-5.83)*
Delay	0.05	0.03	0.04	0.04	0.05	0.06	0.06	0.06
	(0.67)	*(0.44)*	*(0.56)*	*(0.51)*	*(0.64)*	*(0.75)*	*(0.74)*	*(0.75)*
Multi-Trade	-0.45	-0.42	-0.42	-0.41	-0.47	-0.50	-0.34	-0.34
	(-0.93)	*(-0.86)*	*(-0.87)*	*(-0.85)*	*(-0.92)*	*(-0.99)*	*(-0.67)*	*(-0.67)*
LargeTrade	0.66	1.63**	1.40*	1.55**	1.74**	1.49**	1.27*	1.24
	(1.00)	*(2.12)*	*(1.91)*	*(2.01)*	*(2.24)*	*(2.01)*	*(1.70)*	*(1.56)*
Interaction Terms *Index*Insider Type*	NO	NO	NO	NO	NO	NO	YES	YES
VIF (max)	3.268	3.388	3.287	8.690	3.596	3.345	16.536	19.525
N	2,982	2,982	2,982	2,982	2,982	2,982	2,982	2,982
F-test	13.472	12.707	11.275	10.487	8.306	7.902	5.181	5.047
Adj. R^2	4.016%	4.141%	4.289%	4.266%	4.225%	4.426%	5.061%	5.029%
R^2	4.338%	4.495%	4.706%	4.715%	4.803%	5.067%	6.271%	6.271%

Table A. 8: Index Specific OLS-Regressions for Purchases

The left-hand variable is the CAR net of the bid-ask spread (CAR^{net}) over twenty trading days post publication day. Daily abnormal returns (residuals in event and estimation time) are winsorized at the 2% and 98% levels. Returns are adjusted by the return on a portfolio of ten stocks sharing the same size and industry as the event stock (size/industry, see Section 5.1). The right-hand variables are described in Table A. 1 of Appendix A. All continuous variables are centered/scaled (mean 0, sd 1). Test statistics are based on White heteroskedasticity-consistent standard errors. Asterisks ***, **, * equal a significance level of 1%, 5%, and 10%.

+ The intercept in regression (I) is the amount of abnormal returns not explained by the control variables. In regressions (II) the intercept represents transactions by the CEO (all other insider types measure the difference).

Regression	**DAX**		**MDAX**		**SDAX**		**TecDAX**	
	I	**II**	**I**	**II**	**I**	**II**	**I**	**II**
Intercept+	-0.17	-0.53	0.21	-0.30	2.45***	4.53***	4.46***	5.98***
	(-0.37)	*(-0.58)*	*(0.45)*	*(-0.35)*	*(5.24)*	*(5.45)*	*(4.81)*	*(3.59)*
Executive Board Members: CFO		0.49		-1.73		-0.98		-2.34
		(0.31)		*(-1.24)*		*(-0.61)*		*(-1.05)*
Other		0.15		1.29		-1.79		-0.97
		(0.16)		*(1.21)*		*(-1.60)*		*(-0.47)*
Supervisory Board Members: Chair		0.05		1.43		-4.74***		-2.66
		(0.05)		*(1.10)*		*(-4.28)*		*(-1.39)*
Other		1.74		0.93		-3.38		-1.68
		(0.96)		*(0.62)*		*(-1.57)*		*(-0.59)*
Through a Company				0.39		-2.65**		-1.92
				(0.36)		*(-2.52)*		*(-0.84)*
Household Member		2.75		0.71		-2.80**		
		(1.56)		*(0.59)*		*(-2.12)*		
Other Insiders		1.41		0.10		1.19		
		(1.07)		*(0.05)*		*(0.63)*		
log(size)	0.65	0.74	0.75	0.73	-1.68***	-1.64***	1.39	1.54
	(1.47)	*(1.55)*	*(1.49)*	*(1.45)*	*(-3.08)*	*(-2.92)*	*(1.24)*	*(1.27)*
Book-to-Market	1.50	1.54	1.25*	1.15	1.39**	1.10	0.52	0.37
	(0.66)	*(0.67)*	*(1.65)*	*(1.49)*	*(2.06)*	*(1.56)*	*(0.32)*	*(0.22)*
PriorReturn	-0.67	-0.68	0.99	1.03	-1.08*	-1.07*	3.98***	4.10***
	(-0.34)	*(-0.34)*	*(1.49)*	*(1.53)*	*(-1.86)*	*(-1.79)*	*(3.13)*	*(3.21)*
Freefloat	0.56	0.69*	1.19***	1.07***	-0.43	-0.85*	-0.65	-0.59
	(1.49)	*(1.79)*	*(3.03)*	*(2.74)*	*(-1.02)*	*(-1.85)*	*(-0.91)*	*(-0.76)*
Employee-Family-Hold	-0.01	0.14	1.38***	1.26***	0.34	0.00	0.12	0.10
	(-0.03)	*(0.37)*	*(3.70)*	*(3.16)*	*(0.95)*	*(0.01)*	*(0.16)*	*(0.13)*
Debt/Total Assets	-0.73*	-0.59	-0.97***	-1.03***	-0.72*	-0.66*	-1.39	-1.35
	(-1.83)	*(-1.48)*	*(-2.86)*	*(-2.98)*	*(-1.88)*	*(-1.71)*	*(-1.26)*	*(-1.14)*
€-vol/Size	0.96**	1.07**	-0.38	-0.26	-0.47	-0.23	-0.45	-0.34
	(2.14)	*(2.26)*	*(-0.78)*	*(-0.51)*	*(-1.14)*	*(-0.54)*	*(-0.57)*	*(-0.36)*
FinancialCrisis	-1.36	-1.50	-4.92***	-4.98***	-5.29***	-4.94***	-4.48**	-4.34**
	(-1.31)	*(-1.41)*	*(-3.50)*	*(-3.55)*	*(-4.79)*	*(-4.47)*	*(-2.25)*	*(-2.11)*
Delay	0.05	0.05	0.26**	0.22*	-0.24	-0.14	-0.31	-0.25
	(0.38)	*(0.37)*	*(2.24)*	*(1.92)*	*(-1.29)*	*(-0.78)*	*(-1.26)*	*(-0.94)*
Multi-Trade	0.49	0.33	-0.74	-0.70	-1.84*	-1.52	2.49*	2.51*
	(0.66)	*(0.43)*	*(-0.81)*	*(-0.74)*	*(-1.72)*	*(-1.35)*	*(1.76)*	*(1.67)*
LargeTrade	-1.26	-1.97	3.01**	2.97**	1.74	1.68	0.17	0.17
	(-0.93)	*(-1.38)*	*(2.19)*	*(2.11)*	*(1.13)*	*(1.09)*	*(0.06)*	*(0.06)*
VIF (max)	6.765	6.907	3.439	3.505	3.755	3.889	3.889	4.345
N	714	714	1,051	1,051	938	938	279	279
F-test	2.115	1.742	6.897	4.652	5.499	4.824	2.936	2.167
Adj. R^2	1.692%	1.739%	5.819%	5.892%	5.017%	6.843%	7.116%	6.295%
R^2	3.208%	4.082%	6.805%	7.505%	6.132%	8.633%	10.791%	11.688%

Appendix H: Additional Results for Sales - Trading Day

Table A. 9: Equal- and €-Volume-Weight net CARs for Insider Sales Grouped by Insider Type and the Index Membership of the Event Stock

This table shows CARs net of the bid-ask spread (see Table 4 or formula 1, Section 5.3) for insider sales over twenty days post insider trading day. The sample is grouped by the type of the insider and/or the event stock's index membership. Each transaction's individual net CAR is weighted (1) equal [1/N] or (2) by transaction volume (€-vol*) with outliers in volume winsorized at 97.5% for each group individually, see Section 5.4 for details. Daily abnormal returns (residuals in event and estimation time) are winsorized at the 2% and 98% levels. The €-volume is insider's transaction volume (reported price multiplied by the number of stocks traded, adjusted by inflation in prices of December 2012). Returns are adjusted by the return on a portfolio of ten stocks sharing the same size and industry as the event stock (size/industry, see Section 5.1). Test statistics of the GRANK-test by Kolari/Pynnonen (2011) are given below in parentheses (variance is weighted accordingly for weighting procedure (2)). Asterisks ***, **, * equal a significance level of 1%, 5%, and 10%.

	DAX			MDAX			SDAX			TecDAX			OTHERS			ALL		
	N	Equal	€-vol*	N	Equal	€-vol*	N	Equal	€-vol*	N	Equal	€-vol*	N	Equal	€-vol*	N	Equal	€-vol*
Executive Board																		
CEO	20	0.27	1.70	67	-2.60**	-1.57	36	-0.59	-2.47	43	-2.71	-6.36	175	-3.15***	-4.17**	341	-2.51***	-2.37
		(0.05)	*(1.33)*		*(-2.04)*	*(-0.85)*		*(-0.42)*	*(-0.71)*		*(-0.92)*	*(-1.31)*		*(-3.00)*	*(-2.20)*		*(-3.60)*	*(-1.26)*
CFO	10			49	-2.00**	-1.97**	31	2.50	-2.49	55	-5.60**	-7.27**	60	2.11	5.09	205	-1.16*	-3.17***
					(-2.25)	*(-2.41)*		*(1.17)*	*(-1.46)*		*(-2.42)*	*(-2.19)*		*(1.06)*	*(1.22)*		*(-1.66)*	*(-3.66)*
Other	140	0.90**	1.81***	158	-1.77***	-1.82**	115	0.19	2.82*	144	-1.36*	1.32	376	0.79	2.85***	933	-0.03	1.36**
		(2.26)	*(2.67)*		*(-3.20)*	*(-2.04)*		*(0.31)*	*(1.68)*		*(-1.66)*	*(1.19)*		*(1.38)*	*(2.60)*		*(0.08)*	*(2.39)*
Supervisory Board																		
Chair	17			27	-0.25	0.11	20	-0.91	-0.53	14			150	-1.13	3.39	228	-1.34**	0.26
					(-0.75)	*(-0.36)*		*(-0.47)*	*(-0.17)*					*(-0.92)*	*(1.52)*		*(-2.08)*	*(-0.80)*
Deputy	12			13			1			4			83	4.75***	9.32***	113	3.79***	4.87**
														(3.48)	*(3.25)*		*(3.46)*	*(2.53)*
Other	196	-0.11	-1.57**	206	0.73	0.77	72	1.80	4.75**	51	-2.38	-0.51	439	0.10	-0.42*	964	0.19	-1.08***
		(-0.90)	*(-2.51)*		*(1.35)*	*(0.62)*		*(1.08)*	*(2.22)*		*(-1.56)*	*(-0.06)*		*(-1.36)*	*(-1.78)*		*(-0.92)*	*(-3.03)*
Through a Company	5			60	-1.13	-3.00***	44	-2.49	2.35	64	-2.40	-0.08	181	2.90**	5.62**	354	0.52	-0.10
					(-1.48)	*(-3.06)*		*(-0.95)*	*(0.53)*		*(1.17)*	*(0.73)*		*(2.30)*	*(2.32)*		*(1.21)*	*(-0.34)*
Household Member	49	-0.79	0.46	89	-0.88	0.59	141	1.72	1.27	41	0.17	3.98*	345	2.02***	4.82**	665	1.24**	1.70*
		(-0.63)	*(0.34)*		*(-0.45)*	*(1.02)*		*(1.45)*	*(1.15)*		*(0.81)*	*(1.81)*		*(2.66)*	*(2.23)*		*(2.14)*	*(1.85)*
Other Insiders	117	0.80	0.68	34	-3.25	-3.11	22	-0.77	1.51	0			46	-1.12	4.90**	219	-0.39	0.06
		(0.93)	*(0.55)*		*(-1.63)*	*(-0.95)*		*(0.02)*	*(0.61)*					*(-0.13)*	*(2.13)*		*(-0.13)*	*(0.02)*
ALL	566	0.14	-0.07	703	-0.89**	-1.48**	482	0.63	1.06	416	-2.32*	-0.42	1855	0.70	2.07**			
		(0.27)	*(-0.12)*		*(-2.37)*	*(-2.36)*		*(1.20)*	*(1.09)*		*(-1.95)*	*(0.83)*		*(1.47)*	*(2.27)*			

Table A. 10: OLS-Regressions for Sales made with DAX, MDAX, SDAX, and TecDAX stocks

The left-hand variable is the CAR net of the bid-ask spread (CAR^{net}) over twenty trading days post insider trading day. Daily abnormal returns (residuals in event and estimation time) are winsorized at the 2% and 98% levels. Returns are adjusted by the return on a portfolio of ten stocks sharing the same size and industry as the event stock (size/industry, see Section 5.1). The right-hand variables are described in Table A. 1 of Appendix A. All continuous variables are centered/scaled (mean 0, sd 1). Test statistics are based on White heteroskedasticity-consistent standard errors. Asterisks ***, **, * equal a significance level of 1%, 5%, and 10%.

[+] The intercept in regression (I) and (II) is the amount of abnormal returns not explained by the control variables. The intercept equals in regression (III) and (IV): “DAX”; in (V): “CEO”; in (VI) to (VIII) “DAX-CEO”.

Regression	**I**	**II**	**III**	**IV**	**V**	**VI**	**VII**	**VIII**
Intercept[+]	-0.82**	-0.42	-0.85	-3.10***	-1.16	-1.83*	1.50	-1.90
	(-2.22)	*(-1.11)*	*(-1.41)*	*(-4.38)*	*(-1.34)*	*(-1.78)*	*(0.83)*	*(-0.99)*
Executive Board Members: CFO					-0.70	-0.26	-2.81	-3.42
					(-0.55)	*(-0.21)*	*(-1.25)*	*(-1.46)*
Other					0.73	0.93	-0.85	-0.41
					(0.85)	*(1.12)*	*(-0.52)*	*(-0.24)*
Supervisory Board Members: Chair					1.26	1.33	-2.56	-0.90
					(1.42)	*(1.51)*	*(-1.46)*	*(-0.50)*
Other					1.14	1.45	2.06	1.90
					(0.71)	*(0.89)*	*(1.18)*	*(1.11)*
Through a Company					1.03	1.46	1.56	0.34
					(0.93)	*(1.33)*	*(0.70)*	*(0.15)*
Household Member					1.32	1.04	-3.27*	-1.99
					(1.35)	*(1.09)*	*(-1.78)*	*(-1.06)*
Other Insiders					0.12	0.22	-1.67	-1.67
					(0.12)	*(0.22)*	*(-0.91)*	*(-0.88)*
MDAX			0.00	2.58***		0.06	-3.76*	-0.09
			(0.00)	*(3.57)*		*(0.10)*	*(-1.87)*	*(-0.04)*
SDAX			2.03**	6.38***		2.18***	-1.32	3.96
			(2.53)	*(6.08)*		*(2.65)*	*(-0.55)*	*(1.48)*
TecDAX			-1.95***	2.22**		-1.75**	-4.01***	1.56
			(-2.62)	*(2.06)*		*(-2.30)*	*(-4.05)*	*(1.02)*
log(size)		1.37***		2.73***	1.33***			2.75***
		(4.07)		*(5.48)*	*(3.80)*			*(4.73)*
Book-to-Market	0.37	0.62	0.41	0.77	0.55	0.35	0.42	0.72
	(0.31)	*(0.51)*	*(0.34)*	*(0.65)*	*(0.45)*	*(0.29)*	*(0.34)*	*(0.59)*
PriorReturn	-0.26	-0.41	-0.30	-0.37	-0.34	-0.21	-0.30	-0.25
	(-0.27)	*(-0.43)*	*(-0.31)*	*(-0.39)*	*(-0.34)*	*(-0.21)*	*(-0.30)*	*(-0.26)*
Freefloat	0.01	-0.14	0.10	0.26	-0.17	0.09	-0.06	0.17
	(0.04)	*(-0.57)*	*(0.39)*	*(1.03)*	*(-0.66)*	*(0.35)*	*(-0.21)*	*(0.63)*
Employee-Family-Hold	0.12	0.22	-0.07	0.11	0.10	-0.14	-0.20	0.00
	(0.52)	*(0.92)*	*(-0.28)*	*(0.47)*	*(0.42)*	*(-0.56)*	*(-0.77)*	*(0.02)*
Debt/Total Assets	-0.01	-0.06	-0.40*	-0.41*	-0.09	-0.42*	-0.43*	-0.41
	(-0.02)	*(-0.26)*	*(-1.65)*	*(-1.70)*	*(-0.36)*	*(-1.70)*	*(-1.70)*	*(-1.63)*
€-vol/Size	-0.24	0.78**	-0.35	0.60*	0.84**	-0.32	-0.21	0.78**
	(-0.98)	*(2.21)*	*(-1.08)*	*(1.68)*	*(2.31)*	*(-0.97)*	*(-0.61)*	*(2.06)*
FinancialCrisis	-8.07***	-8.03***	-7.25***	-7.12***	-7.85***	-7.27***	-7.41***	-7.07***
	(-3.01)	*(-3.04)*	*(-2.87)*	*(-2.88)*	*(-2.95)*	*(-2.82)*	*(-2.80)*	*(-2.77)*
Delay	0.04	0.07	0.01	0.03	0.05	0.00	-0.01	0.02
	(0.50)	*(0.77)*	*(0.06)*	*(0.30)*	*(0.57)*	*(-0.03)*	*(-0.12)*	*(0.23)*
Multi-Trade	0.15	0.20	0.39	0.39	0.21	0.44	0.41	0.43
	(0.28)	*(0.36)*	*(0.71)*	*(0.72)*	*(0.37)*	*(0.77)*	*(0.70)*	*(0.74)*
LargeTrade	0.46	-1.29*	0.70	-0.97	-1.32*	0.67	0.34	-1.14*
	(0.93)	*(-1.93)*	*(1.13)*	*(-1.46)*	*(-1.96)*	*(1.08)*	*(0.52)*	*(-1.66)*
Interaction Terms *Index*Insider Type*	NO	NO	NO	NO	NO	NO	YES	YES
VIF (max)	4.605	4.696	4.635	6.453	4.723	4.714	23.603	27.737
N	1,864	1,864	1,864	1,864	1,864	1,864	1,864	1,864
F-test	3.641	4.761	5.747	7.569	3.384	4.083	3.192	3.871
Adj. R^2	1.398%	2.173%	3.206%	4.704%	2.251%	3.204%	3.846%	5.118%
R^2	1.927%	2.750%	3.882%	5.421%	3.196%	4.243%	5.601%	6.900%

Table A. 11: Index Specific OLS-Regressions for Sales

The left-hand variable is the CAR net of the bid-ask spread (CAR^{net}) over twenty trading days post insider trading day. Daily abnormal returns (residuals in event and estimation time) are winsorized at the 2% and 98% levels. Returns are adjusted by the return on a portfolio of ten stocks sharing the same size and industry as the event stock (size/industry, see Section 5.1). The right-hand variables are described in Table A. 1 of Appendix A. All continuous variables are centered/scaled (mean 0, sd 1). Test statistics are based on White heteroskedasticity-consistent standard errors. Asterisks ***, **, * equal a significance level of 1%, 5%, and 10%.

+ The intercept in regression (I) is the amount of abnormal returns not explained by the control variables. In regressions (II) the intercept represents transactions by the CEO (all other insider types measure the difference).

Regression	**DAX**		**MDAX**		**SDAX**		**TecDAX**	
	I	**II**	**I**	**II**	**I**	**II**	**I**	**II**
Intercept+	-0.07	0.08	0.44	-0.70	-0.70	-2.41	-1.67*	-1.20
	(-0.11)	*(0.12)*	*(0.72)*	*(-0.61)*	*(-0.75)*	*(-1.10)*	*(-1.81)*	*(-0.64)*
Executive Board Members: CFO				0.78		2.19		-2.83
				(0.51)		*(0.61)*		*(-1.05)*
Other		0.43		0.44		2.51		0.30
		(0.62)		*(0.39)*		*(1.17)*		*(0.16)*
Supervisory Board Members: Chair				2.25*		3.29		-0.59
				(1.96)		*(1.36)*		*(-0.26)*
Other				1.00				
				(0.57)				
Through a Company				1.55		-0.65		2.86
				(1.12)		*(-0.24)*		*(1.00)*
Household Member		-1.73**		1.14		1.06		4.04
		(-2.00)		*(0.76)*		*(0.46)*		*(1.56)*
Other Insiders		-0.92		-0.78		0.23		
		(-1.05)		*(-0.49)*		*(0.08)*		
log(size)	1.03***	1.02***	1.36***	1.39***	1.01	1.13	0.58	0.15
	(3.48)	*(3.02)*	*(3.06)*	*(3.12)*	*(1.13)*	*(1.23)*	*(0.67)*	*(0.15)*
Book-to-Market	-2.03	-2.42	2.49	2.29	-1.90	-2.02	-0.76	-0.65
	(-0.60)	*(-0.67)*	*(1.29)*	*(1.19)*	*(-0.41)*	*(-0.45)*	*(-0.48)*	*(-0.40)*
PriorReturn	2.32	2.97	-2.16	-1.96	2.95	3.14	1.04	0.58
	(0.70)	*(0.84)*	*(-1.62)*	*(-1.47)*	*(0.85)*	*(0.91)*	*(0.74)*	*(0.38)*
Freefloat	0.20	0.09	0.62*	0.54	-0.92	-0.84	0.44	0.27
	(0.80)	*(0.34)*	*(1.76)*	*(1.39)*	*(-1.28)*	*(-1.04)*	*(0.57)*	*(0.37)*
Employee-Family-Hold	-0.70***	-0.83***	0.90**	0.71*	0.73	0.97	-1.10*	-1.56***
	(-2.90)	*(-3.00)*	*(2.33)*	*(1.68)*	*(1.31)*	*(1.52)*	*(-1.93)*	*(-2.75)*
Debt/Total Assets	-0.77**	-0.96**	-0.96***	-0.88**	0.67	0.76	0.68	0.76
	(-2.01)	*(-2.34)*	*(-2.85)*	*(-2.58)*	*(0.99)*	*(1.02)*	*(0.66)*	*(0.73)*
€-vol/Size	0.74	0.85*	-0.39	-0.15	1.18	1.38*	-0.31	-0.22
	(1.49)	*(1.71)*	*(-0.71)*	*(-0.26)*	*(1.64)*	*(1.83)*	*(-0.42)*	*(-0.29)*
FinancialCrisis	3.26	2.81	-5.99*	-5.48*	9.49	11.00	-21.93***	-23.44***
	(1.06)	*(0.86)*	*(-1.91)*	*(-1.72)*	*(0.41)*	*(0.47)*	*(-3.21)*	*(-2.84)*
Delay	0.07	0.10	-0.33**	-0.33**	0.36	0.39	-0.10	-0.24
	(0.66)	*(0.90)*	*(-2.45)*	*(-2.50)*	*(1.54)*	*(1.62)*	*(-0.43)*	*(-1.04)*
Multi-Trade	0.91	1.02	-0.01	0.35	2.63	2.99*	-0.90	-1.59
	(1.41)	*(1.62)*	*(-0.02)*	*(0.34)*	*(1.64)*	*(1.70)*	*(-0.68)*	*(-1.22)*
LargeTrade	-0.97	-1.06	-0.47	-0.46	-2.30	-2.12	0.84	-0.68
	(-1.02)	*(-1.11)*	*(-0.44)*	*(-0.42)*	*(-1.46)*	*(-1.33)*	*(0.45)*	*(-0.35)*
VIF (max)	32.621	34.635	5.119	5.211	4.933	5.093	4.663	4.936
N	455	455	646	646	389	389	373	373
F-test	4.082	3.766	5.636	3.939	2.045	1.637	6.038	5.038
Adj. R^2	6.949%	7.858%	7.326%	7.580%	2.877%	2.714%	12.966%	14.797%
R^2	9.204%	10.700%	8.907%	10.159%	5.631%	6.976%	15.540%	18.462%

Appendix I: Additional Results for Sales - Publication Day

Table A. 12: Equal- and €-Volume-Weight CARs for Insider Sales Grouped by Insider Type and the Index Membership of the Event Stock

This table shows CARs net of the bid-ask spread (see see Table 4 or formula 1, Section 5.3) for insider purchases over twenty days post publication day. All observations with a delay of larger than ten days are excluded. The sample is grouped by the type of the insider and/or the event stock's index membership. Each transaction's individual net CAR is weighted (1) equal [1/N] or (2) by transaction volume (€-vol*), with outliers in volume winsorized at 97.5% for each group individually, see Section 5.4 for details. Daily abnormal returns (residuals in event and estimation time) are winsorized at the 2% and 98% levels. The €-volume is insider's transaction volume (reported price multiplied by the number of stocks traded, adjusted by inflation in prices of December 2012). Returns are adjusted by the return on a portfolio of ten stocks sharing the same size and industry as the event stock (size/industry, see Section 5.1). Test statistics of the GRANK-test by Kolari/Pynnonen (2011) are given below in parentheses (variance is weighted accordingly for weighting procedure (2)). Asterisks ***, **, * equal a significance level of 1%, 5%, and 10%.

	DAX			MDAX			SDAX			TecDAX			OTHERS			ALL		
	N	Equal	€-vol*	N	Equal	€-vol*	N	Equal	€-vol*	N	Equal	€-vol*	N	Equal	€-vol*	N	Equal	€-vol*
Executive Board Members																		
CEO	18			63	-2.60** *(-2.22)*	-1.72 *(-0.67)*	33	-0.68 *(-0.60)*	-2.74 *(-0.87)*	38	-0.36 *(-0.27)*	-1.53 *(-0.29)*	164	-2.61* *(-1.91)*	-3.85* *(-1.72)*	316	-2.01** *(-2.33)*	-2.26 *(-1.63)*
CFO	9			46	-1.32* *(-1.80)*	-2.76*** *(-2.89)*	27	0.01 *(0.50)*	-2.54 *(-0.69)*	52	-4.50** *(-2.35)*	-5.51** *(-2.07)*	56	0.76 *(0.16)*	2.30 *(0.47)*	190	-1.49** *(-2.01)*	-3.30*** *(-3.74)*
Other	136	0.27 *(1.05)*	0.92 *(1.56)*	150	-0.90 *(-1.02)*	-0.98 *(-0.90)*	99	-0.19 *(-0.51)*	3.05** *(2.14)*	137	-1.50* *(-1.67)*	2.54* *(1.73)*	344	0.16 *(-0.45)*	1.06 *(0.09)*	866	-0.31 *(-0.85)*	1.03 *(1.62)*
Supervisory Board Members																		
Chair	17			25	-1.44 *(-1.09)*	-1.57 *(-0.48)*	20	7.45* *(1.95)*	8.87* *(1.66)*	13			137	-1.24 *(-0.62)*	2.90 *(0.73)*	212	-0.52 *(-0.46)*	1.59 *(0.31)*
Deputy	11			12			1			4			77	2.86 *(0.84)*	4.83 *(1.09)*	105	1.96 *(0.53)*	3.13 *(1.56)*
Other	187	-0.64 *(-1.62)*	-1.40*** *(-2.67)*	193	1.64*** *(2.77)*	0.99 *(0.70)*	68	0.72 *(0.62)*	2.40 *(1.34)*	47	-0.61 *(-0.71)*	0.59 *(-0.07)*	412	-2.28* *(-1.85)*	-2.92** *(-2.58)*	907	-0.80 *(-1.29)*	-1.44*** *(-3.57)*
Through a Company	4			56	-1.19 *(-0.55)*	-3.64 *(-1.42)*	40	-4.22 *(-1.04)*	2.68 *(0.29)*	61	-1.58 *(0.27)*	0.34 *(0.60)*	172	-0.91 *(-0.45)*	1.16 *(1.12)*	333	-1.54 *(-0.67)*	-0.59 *(-0.29)*
Household Member	45	-1.20 *(-1.10)*	-0.62 *(-0.61)*	75	1.27 *(0.61)*	3.06 *(1.60)*	130	1.06 *(0.98)*	0.91 *(0.48)*	39	-0.39 *(0.13)*	4.58** *(2.13)*	319	0.94 *(0.01)*	3.20 *(0.71)*	608	0.76 *(0.39)*	1.33 *(0.97)*
Other Insiders	112	0.74 *(0.25)*	0.18 *(-0.45)*	31	-1.81 *(-0.88)*	-1.96 *(-0.52)*	21	-0.94 *(0.10)*	2.77 *(0.93)*	0			43	0.26 *(0.87)*	2.71 *(1.44)*	207	0.09 *(0.10)*	-0.07 *(-0.58)*
ALL	539	-0.28 *(-0.95)*	-0.51 *(-1.43)*	651	-0.18 *(-0.36)*	-1.59* *(-1.75)*	439	0.26 *(0.57)*	1.33 *(1.11)*	391	-1.59* *(-1.66)*	0.64 *(1.11)*	1,724	-0.62 *(-0.98)*	-0.01 *(-0.67)*			

Table A. 13: OLS-Regressions for Sales made with DAX, MDAX, SDAX, and TecDAX stocks

The left-hand variable is the CAR net of the bid-ask spread (CAR^{net}) over twenty trading days post publication day. Daily abnormal returns (residuals in event and estimation time) are winsorized at the 2% and 98% levels. Returns are adjusted by the return on a portfolio of ten stocks sharing the same size and industry as the event stock (size/industry, see Section 5.1). The right-hand variables are described in Table A. 1 of Appendix A. All continuous variables are centered/scaled (mean 0, sd 1). Test statistics are based on White heteroskedasticity-consistent standard errors. Asterisks ***, **, * equal a significance level of 1%, 5%, and 10%.
[+] The intercept in regression (I) and (II) is the amount of abnormal returns not explained by the control variables. The intercept equals in regression (III) and (IV): "DAX"; in (V): "CEO"; in (VI) to (VIII) "DAX-CEO".

Regression	**I**	**II**	**III**	**IV**	**V**	**VI**	**VII**	**VIII**
Intercept[+]	-0.92**	-0.62*	-1.53***	-3.53***	-1.41*	-2.91***	0.62	-2.76
	(-2.56)	*(-1.71)*	*(-2.60)*	*(-4.95)*	*(-1.69)*	*(-2.90)*	*(0.40)*	*(-1.59)*
Executive Board Members: CFO					-0.79	-0.45	-3.53*	-4.13**
					(-0.68)	*(-0.39)*	*(-1.95)*	*(-2.18)*
Other					0.98	1.34	-1.34	-0.95
					(1.16)	*(1.60)*	*(-0.98)*	*(-0.66)*
Supervisory Board Members: Chair					1.47*	1.77**	-2.06	-0.45
					(1.71)	*(2.04)*	*(-1.38)*	*(-0.29)*
Other					-0.38	-0.46	0.71	0.61
					(-0.22)	*(-0.26)*	*(0.37)*	*(0.33)*
Through a Company					0.50	0.77	-0.60	-1.85
					(0.44)	*(0.68)*	*(-0.33)*	*(-0.97)*
Household Member					1.17	1.26	-3.15**	-1.88
					(1.21)	*(1.30)*	*(-2.04)*	*(-1.18)*
Other Insiders					-0.18	0.31	-2.10	-2.16
					(-0.17)	*(0.30)*	*(-1.32)*	*(-1.31)*
MDAX			0.92	3.23***		1.23**	-3.38*	0.27
			(1.61)	*(4.48)*		*(2.08)*	*(-1.83)*	*(0.13)*
SDAX			1.72**	5.62***		2.10**	-1.48	3.84
			(2.10)	*(5.11)*		*(2.50)*	*(-0.64)*	*(1.48)*
TecDAX			-0.67	3.08***		-0.18	-1.77*	3.88***
			(-0.95)	*(2.94)*		*(-0.24)*	*(-1.92)*	*(2.61)*
log(size)		1.05***		2.44***	1.02***			2.81***
		(3.19)		*(4.84)*	*(2.99)*			*(4.85)*
Book-to-Market	0.66	0.86	0.71	1.04	0.76	0.61	0.69	1.00
	(0.68)	*(0.87)*	*(0.73)*	*(1.08)*	*(0.75)*	*(0.61)*	*(0.69)*	*(1.01)*
PriorReturn	-0.11	-0.22	-0.19	-0.24	-0.10	-0.06	-0.16	-0.10
	(-0.14)	*(-0.28)*	*(-0.24)*	*(-0.32)*	*(-0.12)*	*(-0.08)*	*(-0.20)*	*(-0.13)*
Freefloat	-0.20	-0.32	-0.05	0.09	-0.37	-0.05	-0.16	0.06
	(-0.90)	*(-1.40)*	*(-0.21)*	*(0.39)*	*(-1.55)*	*(-0.22)*	*(-0.64)*	*(0.23)*
Employee-Family-Hold	0.17	0.24	0.10	0.25	0.12	0.00	-0.05	0.15
	(0.77)	*(1.11)*	*(0.45)*	*(1.11)*	*(0.53)*	*(-0.01)*	*(-0.20)*	*(0.60)*
Debt/Total Assets	-0.38	-0.43*	-0.63**	-0.64**	-0.45*	-0.63**	-0.68**	-0.66**
	(-1.58)	*(-1.79)*	*(-2.42)*	*(-2.47)*	*(-1.86)*	*(-2.43)*	*(-2.54)*	*(-2.47)*
€-vol/Size	-0.44*	0.34	-0.65**	0.19	0.47	-0.58*	-0.52*	0.47
	(-1.91)	*(1.04)*	*(-2.20)*	*(0.57)*	*(1.39)*	*(-1.93)*	*(-1.67)*	*(1.34)*
FinancialCrisis	-7.54***	-7.50***	-7.06***	-6.94***	-7.21***	-6.83***	-6.98***	-6.65***
	(-2.99)	*(-3.01)*	*(-2.91)*	*(-2.90)*	*(-2.89)*	*(-2.80)*	*(-2.81)*	*(-2.76)*
Delay	0.15**	0.17**	0.12*	0.14**	0.16**	0.12*	0.10	0.13*
	(2.16)	*(2.41)*	*(1.80)*	*(2.03)*	*(2.26)*	*(1.69)*	*(1.47)*	*(1.89)*
Multi-Trade	-0.12	-0.08	0.02	0.04	-0.07	0.03	-0.04	0.02
	(-0.25)	*(-0.15)*	*(0.04)*	*(0.08)*	*(-0.13)*	*(0.05)*	*(-0.07)*	*(0.04)*
LargeTrade	0.68	-0.64	1.12*	-0.36	-0.63	1.24**	1.09*	-0.40
	(1.44)	*(-1.01)*	*(1.93)*	*(-0.56)*	*(-0.97)*	*(2.08)*	*(1.76)*	*(-0.60)*
Interaction Terms *Index*Insider Type*	NO	NO	NO	NO	NO	NO	YES	YES
VIF (max)	4.489	4.584	4.518	6.575	4.613	4.606	23.986	27.690
N	1,741	1,741	1,741	1,741	1,741	1,741	1,741	1,741
F-test	5.082	5.533	5.125	6.611	4.072	3.949	2.887	3.640
Adj. R^2	2.292%	2.786%	2.990%	4.319%	3.080%	3.278%	3.555%	5.042%
R^2	2.854%	3.400%	3.715%	5.089%	4.082%	4.390%	5.440%	6.952%

Table A. 14: Index Specific OLS-Regressions for Sales

The left-hand variable is the CAR net of the bid-ask spread (CAR^{net}) over twenty trading days post publication day. Daily abnormal returns (residuals in event and estimation time) are winsorized at the 2% and 98% levels. Returns are adjusted by the return on a portfolio of ten stocks sharing the same size and industry as the event stock (size/industry, see Section 5.1). The right-hand variables are described in Table A. 1 of Appendix A. All continuous variables are centered/scaled (mean 0, sd 1). Test statistics are based on White heteroskedasticity-consistent standard errors. Asterisks ***, **, * equal a significance level of 1%, 5%, and 10%.

+ The intercept in regression (I) is the amount of abnormal returns not explained by the control variables. In regressions (II) the intercept represents transactions by the CEO (all other insider types measure the difference).

Regression	**DAX**		**MDAX**		**SDAX**		**TecDAX**	
	I	**II**	**I**	**II**	**I**	**II**	**I**	**II**
Intercept+	*-0.31*	0.32	*-0.38*	*-2.01*	*-0.23*	*-1.69*	*-1.38*	*-0.52*
	(-0.52)	*(0.47)*	*(-0.58)*	*(-1.59)*	*(-0.25)*	*(-0.82)*	*(-1.60)*	*(-0.33)*
Executive Board Members: CFO				1.71		1.06		*-3.25*
				(1.06)		*(0.33)*		*(-1.44)*
Other		-0.54		1.63		2.83		*-0.03*
		(-0.82)		*(1.24)*		*(1.31)*		*(-0.02)*
Supervisory Board Members: Chair				2.62**		2.56		0.19
				(2.03)		*(1.12)*		*(0.09)*
Other				*-0.10*				
				(-0.05)				
Through a Company				1.56		0.14		0.15
				(0.93)		*(0.04)*		*(0.06)*
Household Member		*-1.64***		1.37		0.43		1.75
		(-2.00)		*(0.77)*		*(0.20)*		*(0.78)*
Other Insiders		*-1.73**		0.01		0.68		
		(-1.90)		*(0.00)*		*(0.28)*		
log(size)	0.82***	1.06***	0.64	0.70	1.35	1.59*	0.61	0.48
	(2.82)	*(3.27)*	*(1.14)*	*(1.23)*	*(1.51)*	*(1.74)*	*(0.82)*	*(0.55)*
Book-to-Market	*-1.94*	*-2.38*	2.40	2.31	*-0.69*	*-0.70*	*-0.12*	*-0.08*
	(-0.54)	*(-0.58)*	*(1.31)*	*(1.22)*	*(-0.22)*	*(-0.22)*	*(-0.08)*	*(-0.05)*
PriorReturn	2.22	2.98	*-1.58*	*-1.49*	2.31	2.47	0.27	0.03
	(0.63)	*(0.74)*	*(-1.27)*	*(-1.16)*	*(0.97)*	*(1.02)*	*(0.21)*	*(0.02)*
Freefloat	0.31	0.24	0.26	0.19	*-0.91*	*-0.66*	*-0.11*	*-0.15*
	(1.24)	*(0.89)*	*(0.68)*	*(0.45)*	*(-1.21)*	*(-0.81)*	*(-0.18)*	*(-0.25)*
Employee-Family-Hold	*-0.80****	*-0.86****	0.94**	0.81*	1.01*	1.29**	*-1.40****	*-1.65****
	(-3.20)	*(-3.16)*	*(2.37)*	*(1.87)*	*(1.82)*	*(2.12)*	*(-3.00)*	*(-3.32)*
Debt/Total Assets	*-0.70***	*-0.86***	*-0.92***	*-0.86***	*-0.03*	*-0.08*	0.19	0.16
	(-1.99)	*(-2.26)*	*(-2.28)*	*(-2.12)*	*(-0.04)*	*(-0.11)*	*(0.21)*	*(0.17)*
€-vol/Size	0.32	0.55	*-0.87*	*-0.66*	1.46**	1.63**	*-0.29*	*-0.04*
	(0.69)	*(1.18)*	*(-1.41)*	*(-1.04)*	*(2.12)*	*(2.32)*	*(-0.47)*	*(-0.06)*
FinancialCrisis	6.73*	6.30*	*-7.41****	*-7.36***	3.64	4.46	-19.04***	-19.02***
	(1.96)	*(1.83)*	*(-2.68)*	*(-2.56)*	*(0.25)*	*(0.30)*	*(-3.07)*	*(-2.68)*
Delay	0.01	0.03	0.14	0.14	0.16	0.21	*-0.01*	*-0.12*
	(0.10)	*(0.29)*	*(0.95)*	*(0.93)*	*(1.00)*	*(1.26)*	*(-0.05)*	*(-0.65)*
Multi-Trade	0.37	0.56	0.10	0.46	*-0.44*	*-0.29*	0.03	*-0.49*
	(0.66)	*(1.01)*	*(0.10)*	*(0.40)*	*(-0.30)*	*(-0.19)*	*(0.02)*	*(-0.45)*
LargeTrade	*-0.38*	*-0.55*	*-0.06*	0.09	*-2.38*	*-2.33*	1.34	0.57
	(-0.43)	*(-0.63)*	*(-0.05)*	*(0.07)*	*(-1.38)*	*(-1.33)*	*(0.88)*	*(0.35)*
VIF (max)	31.784	33.852	4.976	5.090	4.843	5.013	4.687	4.945
N	437	437	598	598	355	356	350	350
F-test	4.731	4.208	4.341	3.061	1.910	1.504	7.711	5.902
Adj. R^2	8.603%	9.339%	5.800%	5.850%	2.750%	2.358%	17.459%	18.350%
R^2	10.908%	12.250%	7.535%	8.689%	5.772%	7.034%	20.061%	22.094%

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